Lab2_Q1b

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ComS 573

Lab 2

Kanak Choudhury

1 Problem 1

1.1 (b)

For this problem, I have used the following parameter combinations

```
hidden_layers = [1,2,3]
hidden_units = [50, 64, 80]
num_epochs = [10, 50, 100]
btch_size = [128, 200, 300]
learning_rate = [0.1, 0.5, 0.9]
momentum = [.3, .5, 0.9]
loss_func = ['categorical_crossentropy']
data_scaling = ['Standardize', 'Normalize']
activation_func = ['relu', 'tanh']
```

Also used 80% - 20% training - validation data.

[6]:
```
import numpy as np
import pandas as pd
import sklearn.preprocessing
import matplotlib
import keras
import re
import sys
import gc
import time

print('python ' +sys.version)
print('numpy '+ np.__version__)
print('pandas '+ pd.__version__)
print('sklearn '+ sklearn.__version__)
print('matplotlib '+ matplotlib.__version__)
print('keras '+ keras.__version__)
```

```
print('re '+ re.__version__)


from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import Normalizer
from sklearn.metrics import confusion_matrix
from matplotlib import pyplot as plt


from keras import optimizers
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import np_utils
from keras.callbacks import EarlyStopping
from keras.callbacks import ModelCheckpoint
from keras.models import load_model
from itertools import product
```

```
python 3.7.6 (default, Jan  8 2020, 20:23:39) [MSC v.1916 64 bit (AMD64)]
numpy 1.18.1
pandas 1.0.1
sklearn 0.22.1
matplotlib 3.1.3
keras 2.3.1
re 2.2.1
```

[7]:
```
path  = 'D:/ISU/COMS 573 - Machine Learning/HW/Lab2/'
train_model = False

df_tr = pd.read_csv(path+'optdigits.tra',header=None)
X_tr, y_tr = df_tr.loc[:,0:63], df_tr.loc[:,64]
ccat = y_tr.unique().size

df_ts = pd.read_csv(path+'optdigits.tes',header=None)
X_ts,  y_ts  = df_ts.loc[:,0:63],  df_ts.loc[:,64]

scaler = StandardScaler().fit(X_tr)
normalizer = Normalizer().fit(X_tr)

X_tr_std = scaler.transform(X_tr)
X_tr_norm = normalizer.transform(X_tr)


split = 0.8
size = np.shape(X_tr)
nsplit = int(np.floor(split*size[0]))
```

```
y_train1 = np_utils.to_categorical(y_tr, ccat)
y_train = y_train1[0:nsplit,:];
y_val = y_train1[nsplit:size[0],:];
y_test = np_utils.to_categorical(y_ts, ccat)


X_train_std = X_tr_std[0:nsplit,:];
X_val_std = X_tr_std[nsplit:size[0],:];
X_test_std = scaler.transform(X_ts)


X_train_norm = X_tr_norm[0:nsplit,:];
X_val_norm = X_tr_norm[nsplit:size[0],:];
X_test_norm = normalizer.transform(X_ts)
```

[8]:
```
if train_model:
    hidden_layers = [1,2,3]
    hidden_units = [50, 64, 80]
    num_epochs = [10, 50, 100]
    btch_size = [128, 200, 300]
    learning_rate = [0.1, 0.5, 0.9]
    momentum = [.3, .5, 0.9]
    loss_func = ['categorical_crossentropy']
    data_scaling = ['Standardize', 'Normalize']
    activation_func = ['relu', 'tanh']


    def expand_grid(dictionary):
       return pd.DataFrame([row for row in product(*dictionary.values())],
                           columns=dictionary.keys())

    dictionary = {'hidden_layers': hidden_layers,
                  'hidden_units': hidden_units,
                  'num_epochs': num_epochs,
                  'batch_size': btch_size,
                  'learning_rate': learning_rate,
                  'momentum': momentum,
                  'loss_func': loss_func,
                  'data_scaling': data_scaling,
                  'activation_func': activation_func}

    prem1 = expand_grid(dictionary)
    prem1 = prem1[~((prem1['activation_func'] == 'tanh') & (prem1['loss_func']␣
 ↪== 'mean_squared_error'))]
    prem1['time'] = np.NaN
    prem1['train_loss'] = np.NaN
    prem1['validation_loss'] = np.NaN
```

```
    prem1['test_loss'] = np.NaN
    prem1['train_acc'] = np.NaN
    prem1['validation_acc'] = np.NaN
    prem1['test_acc'] = np.NaN
    size_prem1 = prem1.shape
    print(prem1.head())

    ll = 0
    for j in range(0,2):
        if j == 0:
            X_train = X_train_std
            X_val = X_val_std
            X_test = X_test_std
            listind = prem1[prem1['data_scaling'] == 'Standardize'].index.
↪tolist()
        else:
            X_train = X_train_norm
            X_val = X_val_norm
            X_test = X_test_norm
            listind = prem1[prem1['data_scaling'] == 'Normalize'].index.tolist()

        for i in listind:
            start = time. time()
            if prem1.iloc[i,0] == 1:
                model = Sequential()
                model.add(Dense(prem1.iloc[i,1], input_dim=64, activation=prem1.
↪iloc[i,8]))
                model.add(Dense(ccat, activation='softmax'))

            elif prem1.iloc[i,0] == 2:
                model = Sequential()
                model.add(Dense(prem1.iloc[i,1], input_dim=64, activation=prem1.
↪iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(ccat, activation='softmax'))

            elif prem1.iloc[i,0] == 3:
                model = Sequential()
                model.add(Dense(prem1.iloc[i,1], input_dim=64, activation=prem1.
↪iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(ccat, activation='softmax'))

            else:
                model = Sequential()
```

```
                model.add(Dense(prem1.iloc[i,1], input_dim=64, activation=prem1.
↪iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(prem1.iloc[i,1], activation=prem1.iloc[i,8]))
                model.add(Dense(ccat, activation='softmax'))


            es = EarlyStopping(monitor='val_accuracy', mode='max', verbose=0,␣
↪patience=200)
            mc = ModelCheckpoint('best_model', monitor='val_accuracy',␣
↪mode='max', verbose=0, save_best_only=True)


            optimizer1 = optimizers.SGD(lr=prem1.iloc[i,4], momentum=prem1.
↪iloc[i,5])
            model.compile(optimizer=optimizer1, loss=prem1.iloc[i,6],␣
↪metrics=['accuracy'])
            fit1 = model.fit(X_train,y_train, batch_size=prem1.iloc[i,3],␣
↪epochs=prem1.iloc[i,2],
                             validation_data=(X_val,y_val), callbacks=[es, mc],␣
↪verbose = 0)
            fit = load_model('best_model')
            end = time.time()
            train_accuracy = fit.evaluate(X_train, y_train, verbose=0)
            val_accuracy = fit.evaluate(X_val, y_val, verbose=0)
            test_accuracy = fit.evaluate(X_test, y_test, verbose=0)
            prem1.iloc[i, 9:16] = [end-start, train_accuracy[0],␣
↪val_accuracy[0], test_accuracy[0],
                                  train_accuracy[1], val_accuracy[1],␣
↪test_accuracy[1]]


            del model, es, mc, optimizer1, fit, fit1
            gc.collect()
            ll = ll+1
            sys.stdout.write("\r Progress: %.2f%%" %round(float(ll)/
↪size_prem1[0]*100,2))
            sys.stdout.flush()
else:
    print('skiped model fit')
```

skiped model fit

[9]:
```
if train_model:
    prem1.to_csv (path+'res_1b.csv', index = False, header=True)
```

```python
else:
    prem221 = pd.read_csv(path+'res_1b.csv',header=0)
    prem222 = pd.read_csv(path+'res_1a.csv',header=0)

    prem222 = prem222[((prem222['activation_func']=='relu') &␣
 ↪(prem222['loss_func']=='categorical_crossentropy'))]
    prem1 = prem221.append(prem222)
    del prem221, prem222


top10_relu = prem1[prem1['activation_func'] == 'relu'].nlargest(10,'test_acc')
top10_tanh = prem1[prem1['activation_func'] == 'tanh'].nlargest(10,'test_acc')
print('\n Best 10 hyper-parameter combination for tanh:\n', round(top10_tanh,␣
 ↪4))
print('\n Best 10 hyper-parameter combination for relu:\n', round(top10_relu,␣
 ↪4))

plt.hist([prem1[prem1['activation_func'] == 'tanh'].iloc[:,9],
          prem1[prem1['activation_func'] == 'relu'].iloc[:,9]],
         bins=300, density=True, alpha=0.5, label=['tanh', 'relu'])
plt.legend(loc='upper right')
plt.title('Distribution of time to fit models')
plt.xlim(0, 200)
plt.show()

plt.hist([prem1[prem1['activation_func'] == 'tanh'].iloc[:,15],
          prem1[prem1['activation_func'] == 'relu'].iloc[:,15]],
         density=True, alpha=0.5, label=['tanh', 'relu'])
plt.legend(loc='upper left')
plt.title('Distribution of test accuracy')
plt.show()
```

```
 Best 10 hyper-parameter combination for tanh:
      hidden_layers  hiden_units  num_epochs  batch_size  learning_rate  \
1210              3           64          50         200            0.1
892               2           80          50         200            0.5
928               2           80         100         128            0.5
1220              3           64          50         200            0.9
800               2           64         100         300            0.5
1090              3           50         100         128            0.5
1270              3           64         100         200            0.5
623               2           50         100         200            0.5
946               2           80         100         200            0.5
1106              3           50         100         200            0.5

     momentum                 loss_func data_scaling activation_func  \
```

1210	0.9	categorical_crossentropy	Standardize	tanh
892	0.9	categorical_crossentropy	Standardize	tanh
928	0.9	categorical_crossentropy	Standardize	tanh
1220	0.5	categorical_crossentropy	Standardize	tanh
800	0.5	categorical_crossentropy	Standardize	tanh
1090	0.9	categorical_crossentropy	Standardize	tanh
1270	0.9	categorical_crossentropy	Standardize	tanh
623	0.9	categorical_crossentropy	Normalize	tanh
946	0.9	categorical_crossentropy	Standardize	tanh
1106	0.5	categorical_crossentropy	Standardize	tanh

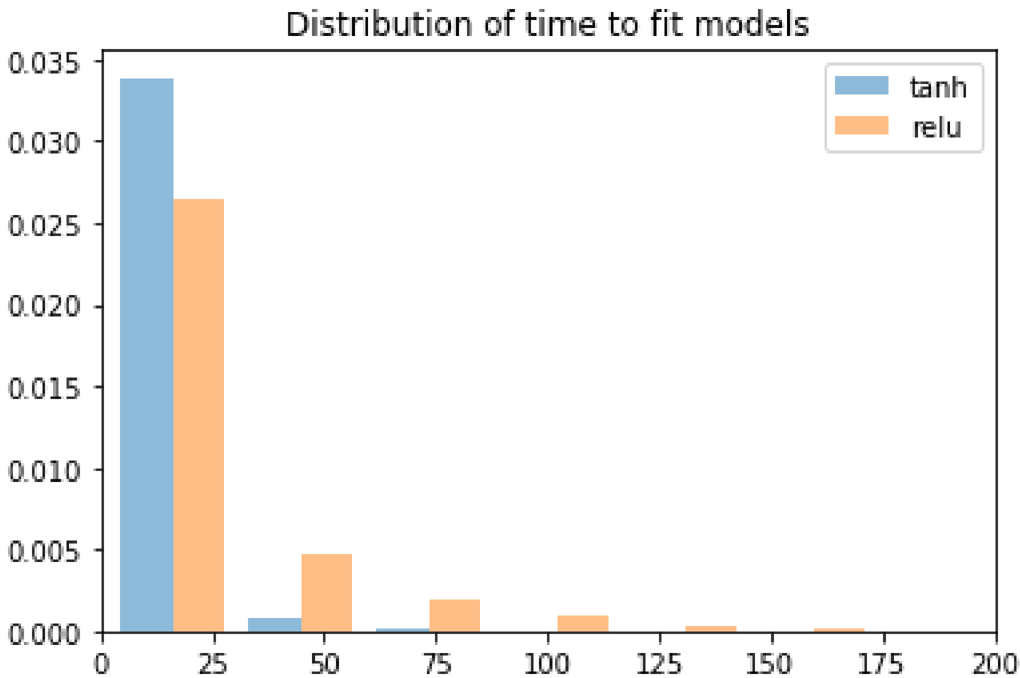
	time	train_loss	validation_loss	test_loss	train_acc \
1210	7.0783	0.0016	0.0789	0.1434	1.0000
892	5.1075	0.0041	0.0738	0.1368	0.9993
928	8.9442	0.0001	0.0987	0.1527	1.0000
1220	5.9771	0.0009	0.0469	0.1319	1.0000
800	6.6442	0.0088	0.0615	0.1275	1.0000
1090	9.1255	0.0001	0.0843	0.1729	1.0000
1270	8.4695	0.0000	0.1137	0.1811	1.0000
623	10.4227	0.0028	0.0558	0.1528	1.0000
946	7.5301	0.0014	0.0753	0.1495	1.0000
1106	7.9243	0.0087	0.0713	0.1158	0.9997

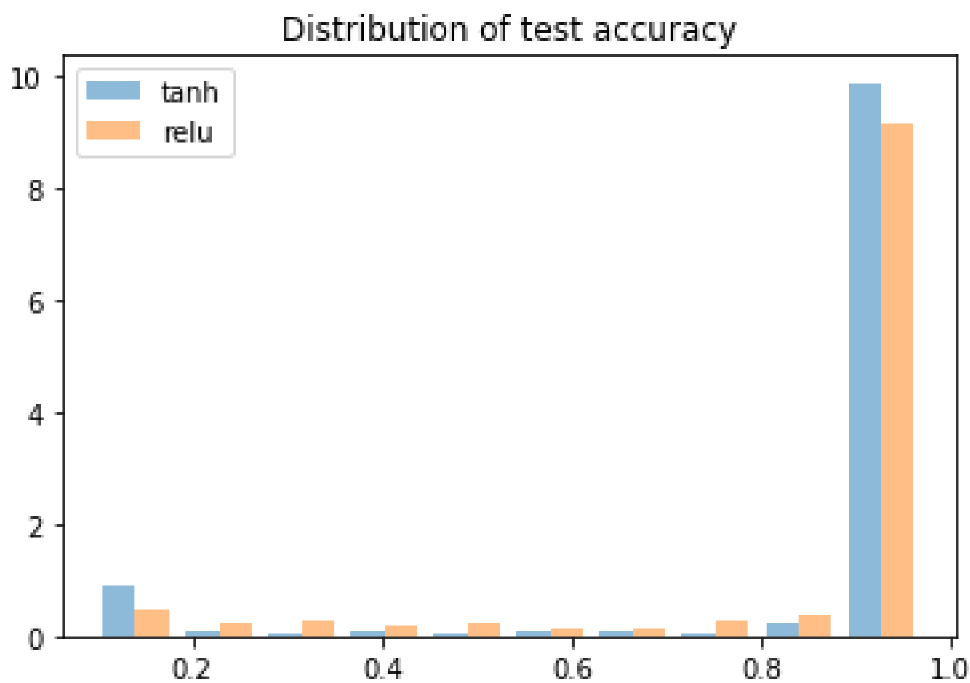
	validation_acc	test_acc
1210	0.9817	0.9699
892	0.9804	0.9694
928	0.9856	0.9688
1220	0.9869	0.9677
800	0.9856	0.9672
1090	0.9856	0.9672
1270	0.9804	0.9672
623	0.9908	0.9666
946	0.9830	0.9666
1106	0.9817	0.9666

Best 10 hyper-parameter combination for relu:

	hidden_layers	hiden_units	num_epochs	batch_size	learning_rate \
1430	2	64	50	128	0.9
486	1	64	50	200	0.5
782	1	80	50	128	0.9
1290	2	50	100	300	0.9
1522	2	64	100	128	0.1
2766	3	80	50	200	0.9
2854	3	80	100	200	0.1
2823	3	80	100	128	0.5
1427	2	64	50	128	0.5
1571	2	64	100	200	0.5

	momentum	loss_func	data_scaling	activation_func	time	train_loss	validation_loss	test_loss	train_acc	validation_acc	test_acc
1430	0.3	categorical_crossentropy	Standardize	relu	5.8781	0.0013	0.0781	0.1324	1.0000	0.9869	0.9699
486	0.5	categorical_crossentropy	Standardize	relu	5.0245	0.0110	0.0740	0.1119	0.9997	0.9817	0.9694
782	0.3	categorical_crossentropy	Standardize	relu	4.8596	0.0016	0.0455	0.1397	1.0000	0.9882	0.9672
1290	0.5	categorical_crossentropy	Standardize	relu	6.5375	0.0030	0.0699	0.1386	1.0000	0.9856	0.9672
1522	0.9	categorical_crossentropy	Standardize	relu	8.1272	0.0019	0.0760	0.1469	1.0000	0.9830	0.9672
2766	0.5	categorical_crossentropy	Standardize	relu	8.6308	0.0009	0.0869	0.1967	1.0000	0.9817	0.9672
2854	0.9	categorical_crossentropy	Standardize	relu	17.2453	0.0011	0.0811	0.1428	1.0000	0.9843	0.9672
2823	0.3	categorical_crossentropy	Normalize	relu	61.7760	0.0106	0.0743	0.1560	0.9974	0.9856	0.9666
1427	0.9	categorical_crossentropy	Normalize	relu	64.7441	0.0025	0.0735	0.1666	0.9997	0.9869	0.9661
1571	0.9	categorical_crossentropy	Normalize	relu	32.2653	0.0020	0.0926	0.1864	0.9997	0.9869	0.9661





[10]:
```
aaa = prem1[prem1['activation_func'] == 'tanh'].iloc[:,9]
bbb = prem1[prem1['activation_func'] == 'relu'].iloc[:,9]
```

```
print("Mean and Variance of fitted time:\n tanh: Mean = %.2f, \
var = %.2f\n relu: Mean = %.2f, \
var = %.2f\n" %(np.mean(aaa), np.var(aaa), np.mean(bbb), np.var(bbb)))

aaa = prem1[prem1['activation_func'] == 'tanh'].iloc[:,15]
bbb = prem1[prem1['activation_func'] == 'relu'].iloc[:,15]
print("Mean and Variance of test accuracy:\n tanh: Mean = %.4f, \
var = %.4f\n relu: Mean = %.4f, \
var = %.4f\n" %(np.mean(aaa), np.var(aaa), np.mean(bbb), np.var(bbb)))
```

```
Mean and Variance of fitted time:
 tanh: Mean = 8.74, var = 129.97
 relu: Mean = 37.11, var = 70030.07

Mean and Variance of test accuracy:
 tanh: Mean = 0.8627, var = 0.0587
 relu: Mean = 0.8520, var = 0.0515
```

[11]:

```
for i in range(2):
    if i==0:
        top10 = top10_tanh
        print("\n Results For tanh Activation Function")
        print("******************************************\n")
    else:
        top10 = top10_relu
        print("\n Results For relu Activation Function")
        print("******************************************\n")


    if top10.iloc[0,7] == 'Standardize':
        X_train = X_train_std
        X_val = X_val_std
        X_test = X_test_std
    else:
        X_train = X_train_norm
        X_val = X_val_norm
        X_test = X_test_norm


    start = time. time()
    if top10.iloc[0,0] == 1:
        model = Sequential()
        model.add(Dense(top10.iloc[0,1], input_dim=64, activation=top10.
↪iloc[0,8]))
        model.add(Dense(ccat, activation='softmax'))
```

```
    elif top10.iloc[0,0] == 2:
        model = Sequential()
        model.add(Dense(top10.iloc[0,1], input_dim=64, activation=top10.
↪iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(ccat, activation='softmax'))

    elif top10.iloc[0,0] == 3:
        model = Sequential()
        model.add(Dense(top10.iloc[0,1], input_dim=64, activation=top10.
↪iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(ccat, activation='softmax'))

    else:
        model = Sequential()
        model.add(Dense(top10.iloc[0,1], input_dim=64, activation=top10.
↪iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(top10.iloc[0,1], activation=top10.iloc[0,8]))
        model.add(Dense(ccat, activation='softmax'))

    es = EarlyStopping(monitor='val_accuracy', mode='max', verbose=0,␣
↪patience=200)
    mc = ModelCheckpoint('best_model', monitor='val_accuracy', mode='max',␣
↪verbose=0, save_best_only=True)

    optimizer1 = optimizers.SGD(lr=top10.iloc[0,4], momentum=top10.iloc[0,5])
    model.compile(optimizer=optimizer1, loss=top10.iloc[0,6],␣
↪metrics=['accuracy'])
    fit1 = model.fit(X_train,y_train, batch_size=top10.iloc[0,3], epochs=top10.
↪iloc[0,2],
                    validation_data=(X_val,y_val), callbacks=[es, mc], verbose␣
↪= 0)
    fit = load_model('best_model')
    end = time.time()

    train_accuracy = fit.evaluate(X_train, y_train, verbose=0)
    val_accuracy = fit.evaluate(X_val, y_val, verbose=0)
    test_accuracy = fit.evaluate(X_test, y_test, verbose=0)
    final_res = [end-start, train_accuracy[0], val_accuracy[0],␣
↪test_accuracy[0],
                train_accuracy[1], val_accuracy[1], test_accuracy[1]]
```

```python
    if top10.iloc[0,7] == 'Standardize':
        X_train11 = X_tr_std
        X_test = X_test_std
        y_train11 = y_train1
    else:
        X_train11 = X_tr_norm
        X_test = X_test_norm
        y_train11 = y_train1

    print("For hyper-parameters:\n",top10.iloc[0,:])
    print("\n Time needed: %.2f" % (end-start))
    scores = fit.evaluate(X_test, y_test, verbose=0)
    print("\n Test Accuracy: %.2f%%" % (scores[1]*100))

    A = fit.predict(X_train11)
    cm = confusion_matrix(y_train11.argmax(axis=1), A.argmax(axis=1))
    print("\n Train confusion matrix: \n", cm)
    acc_train = np.diagonal(cm)/cm.sum(axis=1)
    print("\n Class Accuracy for Training Data is:")
    for i in range(10):
        print('Class %d: %.2f%%' %(i, acc_train[i]*100))

    A = fit.predict(X_test)
    cm = confusion_matrix(y_test.argmax(axis=1), A.argmax(axis=1))
    print("\n Test confusion matrix: \n", cm)
    acc_test = np.diagonal(cm)/cm.sum(axis=1)
    print("\n Class Accuracy for Testing Data is:")
    for i in range(10):
        print('Class %d: %.2f%%' %(i, acc_test[i]*100))
    print("**********************************\n")
```

```
 Results For tanh Activation Function
******************************************

For hyper-parameters:
 hidden_layers                          3
hiden_units                            64
num_epochs                             50
batch_size                            200
learning_rate                         0.1
momentum                              0.9
loss_func        categorical_crossentropy
data_scaling                  Standardize
activation_func                      tanh
time                              7.07828
train_loss                     0.00162618
```

```
validation_loss                   0.0788507
test_loss                           0.14345
train_acc                                 1
validation_acc                     0.981699
test_acc                            0.96995
Name: 1210, dtype: object

 Time needed: 5.49

 Test Accuracy: 95.16%

 Train confusion matrix:
 [[374   0   0   0   1   0   1   0   0   0]
 [  0 384   0   0   0   0   1   0   2   2]
 [  1   0 378   1   0   0   0   0   0   0]
 [  0   1   0 384   0   3   0   0   0   1]
 [  0   0   0   0 384   0   1   1   0   1]
 [  0   0   1   0   1 370   0   0   0   4]
 [  0   2   0   0   1   0 373   0   1   0]
 [  0   0   0   1   0   1   0 385   0   0]
 [  0   2   0   0   0   0   1   0 376   1]
 [  0   1   0   2   6   1   0   0   2 370]]

 Class Accuracy for Training Data is:
Class 0: 99.47%
Class 1: 98.71%
Class 2: 99.47%
Class 3: 98.71%
Class 4: 99.22%
Class 5: 98.40%
Class 6: 98.94%
Class 7: 99.48%
Class 8: 98.95%
Class 9: 96.86%

 Test confusion matrix:
 [[177   0   0   0   1   0   0   0   0   0]
 [  0 175   0   0   0   0   4   0   1   2]
 [  0   5 164   6   0   0   1   0   1   0]
 [  0   0   5 176   0   1   0   0   0   1]
 [  0   1   0   0 178   0   0   0   2   0]
 [  0   0   0   1   0 179   1   0   0   1]
 [  0   1   0   0   2   0 177   0   1   0]
 [  0   0   0   0   2  11   0 163   1   2]
 [  0   7   0   1   0   3   1   0 154   8]
 [  0   1   1   2   3   3   0   0   3 167]]

 Class Accuracy for Testing Data is:
```

```
Class 0: 99.44%
Class 1: 96.15%
Class 2: 92.66%
Class 3: 96.17%
Class 4: 98.34%
Class 5: 98.35%
Class 6: 97.79%
Class 7: 91.06%
Class 8: 88.51%
Class 9: 92.78%
**********************************


 Results For relu Activation Function
******************************************

For hyper-parameters:
 hidden_layers                                2
hiden_units                                 64
num_epochs                                  50
batch_size                                 128
learning_rate                              0.9
momentum                                   0.3
loss_func           categorical_crossentropy
data_scaling                     Standardize
activation_func                         relu
time                                 5.87814
train_loss                        0.00131139
validation_loss                    0.0780658
test_loss                           0.132371
train_acc                                  1
validation_acc                      0.986928
test_acc                             0.96995
Name: 1430, dtype: object

 Time needed: 5.81

 Test Accuracy: 96.72%

 Train confusion matrix:
 [[376   0   0   0   0   0   0   0   0   0]
 [  0 389   0   0   0   0   0   0   0   0]
 [  0   0 378   1   0   0   1   0   0   0]
 [  0   1   0 387   0   1   0   0   0   0]
 [  0   0   0   0 386   0   1   0   0   0]
 [  0   0   0   0   0 376   0   0   0   0]
 [  0   0   0   0   0   0 377   0   0   0]
 [  0   0   0   1   0   1   0 385   0   0]
```

```
 [  0   0   0   1   0   0   0   0 379   0]
 [  0   0   0   1   0   0   0   0   1 380]]

 Class Accuracy for Training Data is:
Class 0: 100.00%
Class 1: 100.00%
Class 2: 99.47%
Class 3: 99.49%
Class 4: 99.74%
Class 5: 100.00%
Class 6: 100.00%
Class 7: 99.48%
Class 8: 99.74%
Class 9: 99.48%

 Test confusion matrix:
 [[178   0   0   0   0   0   0   0   0   0]
 [  0 179   0   0   0   0   3   0   0   0]
 [  0   1 171   4   0   0   0   0   1   0]
 [  1   0   7 172   0   1   0   0   0   2]
 [  0   2   0   0 176   0   0   0   3   0]
 [  0   1   0   0   0 180   0   0   0   1]
 [  0   1   0   0   3   0 176   0   1   0]
 [  0   0   0   0   1   2   0 173   1   2]
 [  0   4   0   2   1   0   0   0 160   7]
 [  0   0   1   1   0   4   0   0   1 173]]

 Class Accuracy for Testing Data is:
Class 0: 100.00%
Class 1: 98.35%
Class 2: 96.61%
Class 3: 93.99%
Class 4: 97.24%
Class 5: 98.90%
Class 6: 97.24%
Class 7: 96.65%
Class 8: 91.95%
Class 9: 96.11%
**********************************
```

Based on the time distribution, *tanh* activation function takes shorter time than *relu* activation function that can be confirmed by the smaller mean and variance for *tanh* than *relu*.

However, based on test accuracy distributions, *tanh* activation function is less sensitive on the hyper-parameters than the *relu* activation function for this data because from the histogram we can see that for most hyper-parameters combination *tanh* activation function produces test accuracy that is close to highest test accuracy. Additionally, the average test accuracy for all combinations of hyper-parameter is higher for *tanh* compare to *relu* and lower variance for *tanh* than *relu*. This also supports that *tanh* activation function is less sensitive on the hyper-parameters than the *relu* for this data. Note that, for this experiment, I have considered same hyper-parameter combinations for *tanh* and *relu* activation functions.

It is found that using *relu* activation function with 2 hidden layers, 64 units, number of epochs 50, batch size 128, learning rate 0.9 and momentum 0.3 has the highest test accuracy (around 96.00%), although *tanh* activation function gives almost same test accuracy. Note that, this model was fitted based on only 1-fold cross validation with no repeated sample. It might be different if we use repeated k fold cross validation.

Training accuracy for all classes are almost 100%. However, test accuracy for all classes are around 96%. Class 0 has the highest test accuracy and class 8 has the lowest accuracy for *relu* activation function. Also, almost similar pattern has been found for the *tanh* activation function. Overall classification accuracy, class accuracy, and confusion matrix for both training and testing data are given in above tables.

1.2 Important References:

1. https://towardsdatascience.com/building-our-first-neural-network-in-keras-bdc8abbc17f5
2. https://towardsdatascience.com/building-a-deep-learning-model-using-keras-1548ca149d37
3. https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/
4. https://towardsdatascience.com/building-a-convolutional-neural-network-cnn-in-keras-329fbbadc5f5
5. https://towardsdatascience.com/convolutional-neural-networks-for-beginners-practical-guide-with-python-and-keras-dc688ea90dca

[ ]:

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