MACHINE LEARNING ASSIGNMENT

Classification for Mushrooms

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1. INTRODUCTION

Although this dataset was originally contributed to the UCI Machine Learning repository nearly 30 years ago, mushroom hunting is enjoying new peaks in popularity. The dataset helps to learn which features spell certain death and which are most palatable in this dataset of mushroom characteristics. The purpose of this documentation is to come up with the most accurate model to classify the mushroom verities. Hence, this documentation contains a classification problem to classify the mushrooms whether they are diet able or poisons. here I will be using Feed Forward Neural Network to classify them into given two categories. At the end of the document the accuracy level and the error has been plated in terms of different optimizations.

2. USED DATASET

2.1 Description of dataset

This dataset includes descriptions of hypothetical samples corresponding to 23 species of gilled mushrooms in the Agaricus and Lepiota Family Mushroom drawn from The Audubon Society Field Guide to North American Mushrooms (1981). Each species is identified as definitely edible, definitely poisonous, or of unknown edibility and not recommended. This latter class was combined with the poisonous one. The following link is for the hosted environment of the dataset. The data set consists with 8124 samples.

https://www.kaggle.com/uciml/mushroom-classification

2.2 Features & Labels

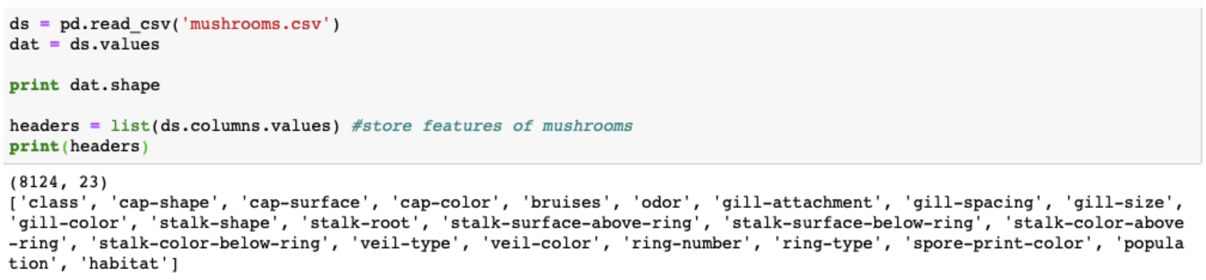
There are 22 features has been taken into consideration.

- cap-shape: bell=b,conical=c,convex=x,flat=f, knobbed=k,sunken=s
- cap-surface: fibrous=f,grooves=g,scaly=y,smooth=s
- cap-color: brown=n,buff=b,cinnamon=c,gray=g,green=r,pink=p,purple=u,red=e,white=w,yellow=y
- bruises: bruises=t,no=f
- odor: almond=a,anise=l,creosote=c,fishy=y,foul=f,musty=m,none=n,pungent=p,spicy=s
- gill-attachment: attached=a,descending=d,free=f,notched=n
- gill-spacing: close=c,crowded=w,distant=d
- gill-size: broad=b,narrow=n
- gill-color: black=k,brown=n,buff=b,chocolate=h,gray=g, green=r,orange=o,pink=p,purple=u,red=e,white=w,yellow=y
- stalk-shape: enlarging=e,tapering=t
- stalk-root: bulbous=b,club=c,cup=u,equal=e,rhizomorphs=z,rooted=r,missing=?
- stalk-surface-above-ring: fibrous=f,scaly=y,silky=k,smooth=s
- stalk-surface-below-ring: fibrous=f,scaly=y,silky=k,smooth=s
- stalk-color-above-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o,pink=p,red=e, white=w,yellow=y

- stalk-color-below-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o,pink=p,red=e, white=w,yellow=y
- veil-type: partial=p,universal=u
- veil-color: brown=n,orange=o,white=w,yellow=y
- ring-number: none=n,one=o,two=t
- ring-type: cobwebby=c,evanescent=e,flaring=f,large=l,none=n,pendant =p,sheathing=s,zone=z
- spore-print-color: black=k,brown=n,buff=b,chocolate=h,green=r,orange=o,pur ple=u,white=w,yellow=y
- population: abundant=a,clustered=c,numerous=n,scattered=s,several=v, solitary=y
- habitat: grasses=g,leaves=l,meadows=m,paths=p,urban=u,waste=w, woods=d
-

In addition to these 22 features, the labels/classes are

- edible=e
- poisonous=p



```
ds = pd.read_csv('mushrooms.csv')
dat = ds.values

print dat.shape

headers = list(ds.columns.values) #store features of mushrooms
print(headers)
```

```
(8124, 23)
['class', 'cap-shape', 'cap-surface', 'cap-color', 'bruises', 'odor', 'gill-attachment', 'gill-spacing', 'gill-size',
'gill-color', 'stalk-shape', 'stalk-root', 'stalk-surface-above-ring', 'stalk-surface-below-ring', 'stalk-color-above
-ring', 'stalk-color-below-ring', 'veil-type', 'veil-color', 'ring-number', 'ring-type', 'spore-print-color', 'popula
tion', 'habitat']
```

Figure 2.2.1 specify features

3. METHODOLOGY

3.1. Feed Forward Neural Network

A feedforward neural network is an artificial neural network wherein connections between the nodes do not form a cycle. As such, it is different from recurrent neural networks. The feedforward neural network was the first and the simplest type of artificial neural network devised. Following is the sketch to my suggested model.

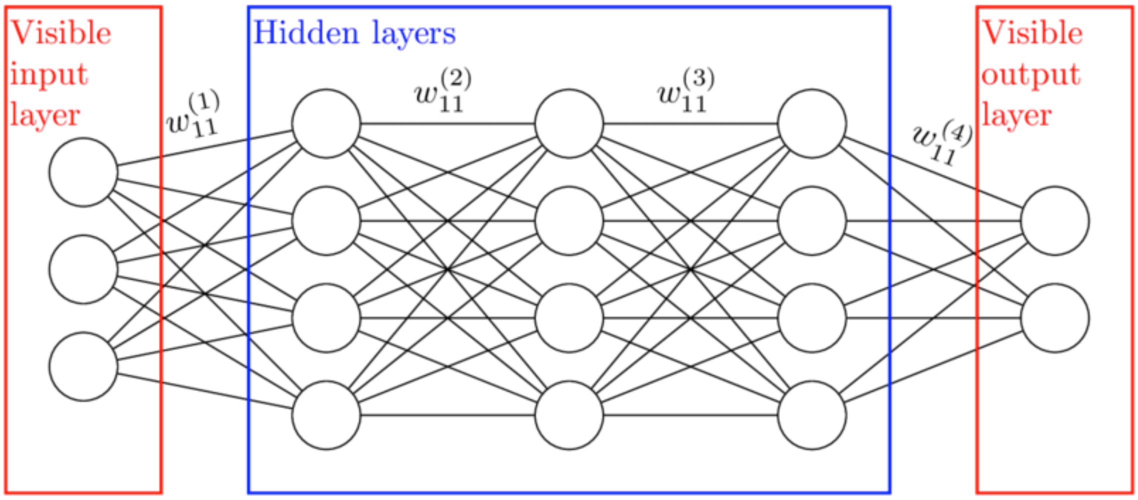


Figure 3.1.1 Neural Network Model

22– neurons for the input layer

11- neurons in the first hidden layer

11- neurons in the second hidden layer

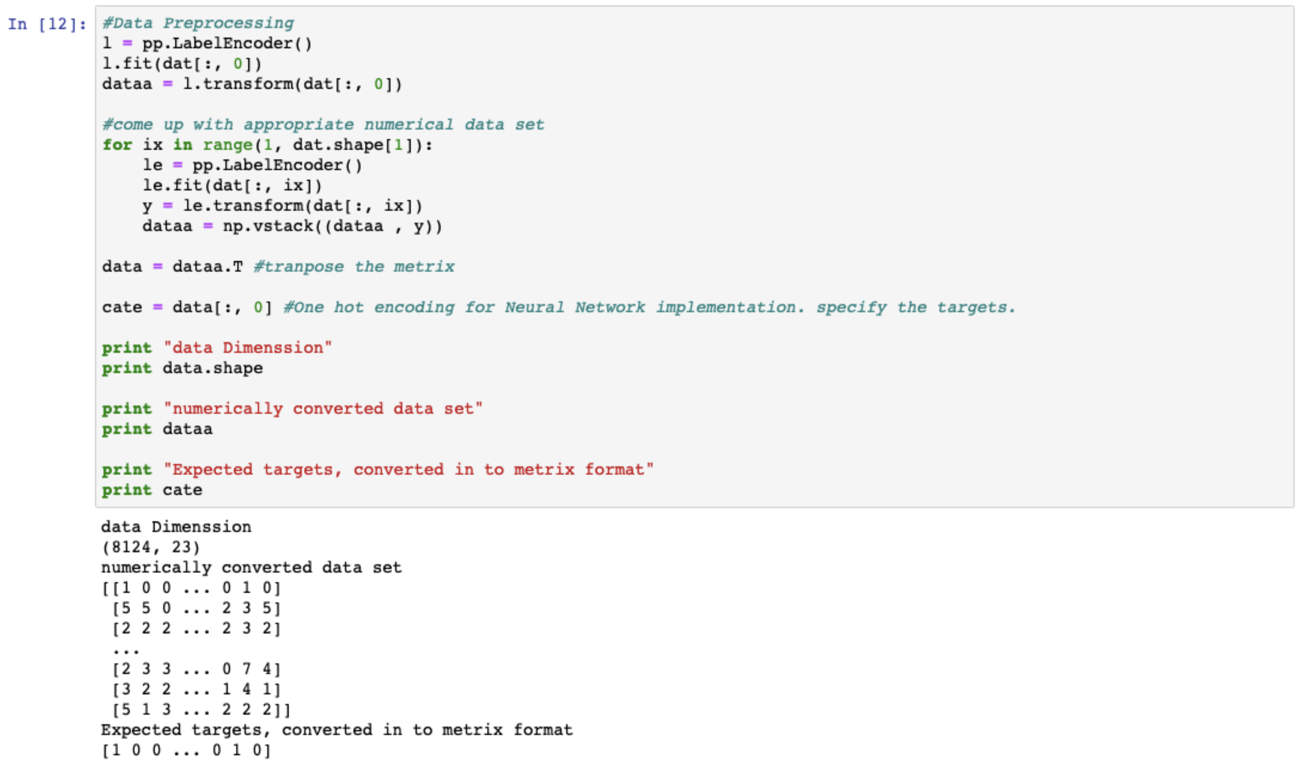
2– neurons for the output layer

Here I have used the sequential neural network model to create my model with three hidden dense layers. I have used two different activation functions (“relu” and “softwamx”) for the hidden layers and “adam” is the optimization technique that I have used while categorical cross entropy is the error loss calculation function. Since there are only 2 labels are available, my model has three output neurons which gives the probabilities as the output. The neuron which gives the highest probability would be taken as the positive class.

4. Implementation

4.1 Data Processing

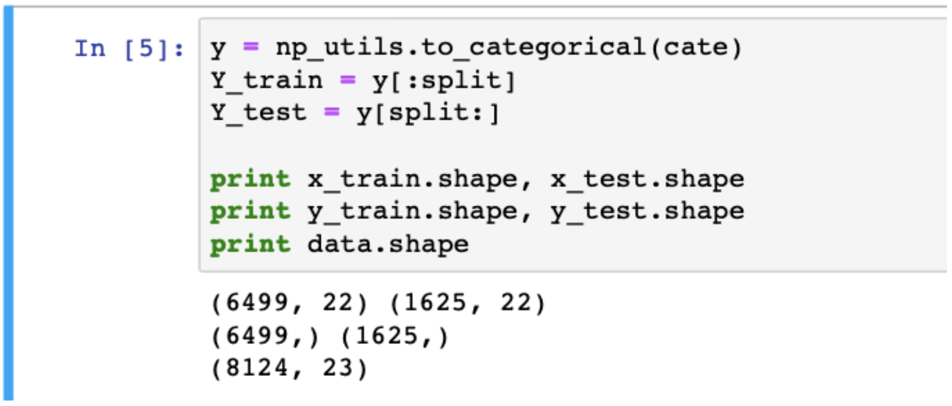
The original data set has characteristic values but we need to provide numerical values to the feed forward neural network. Therefore, the data set has been looped and came up with an appropriate matrix that can be considered as the input data set. The target values also have been converted into appropriate matrix.



```
In [12]: #Data Preprocessing
         l = pp.LabelEncoder()
         l.fit(dat[:, 0])
         dataa = l.transform(dat[:, 0])

         #come up with appropriate numerical data set
         for ix in range(1, dat.shape[1]):
             le = pp.LabelEncoder()
             le.fit(dat[:, ix])
             y = le.transform(dat[:, ix])
             dataa = np.vstack((dataa , y))

         data = dataa.T #tranpose the metrix

         cate = data[:, 0] #One hot encoding for Neural Network implementation. specify the targets.

         print "data Dimenssion"
         print data.shape

         print "numerically converted data set"
         print dataa

         print "Expected targets, converted in to metrix format"
         print cate

data Dimenssion
(8124, 23)
numerically converted data set
[[1 0 0 ... 0 1 0]
 [5 5 0 ... 2 3 5]
 [2 2 2 ... 2 3 2]
 ...
 [2 3 3 ... 0 7 4]
 [3 2 2 ... 1 4 1]
 [5 1 3 ... 2 2 2]]
Expected targets, converted in to metrix format
[1 0 0 ... 0 1 0]
```

Figure 4.1.1 Covert into a numerical array

After converting them into appropriate array dimensions they have been converted into NumPy arrays.

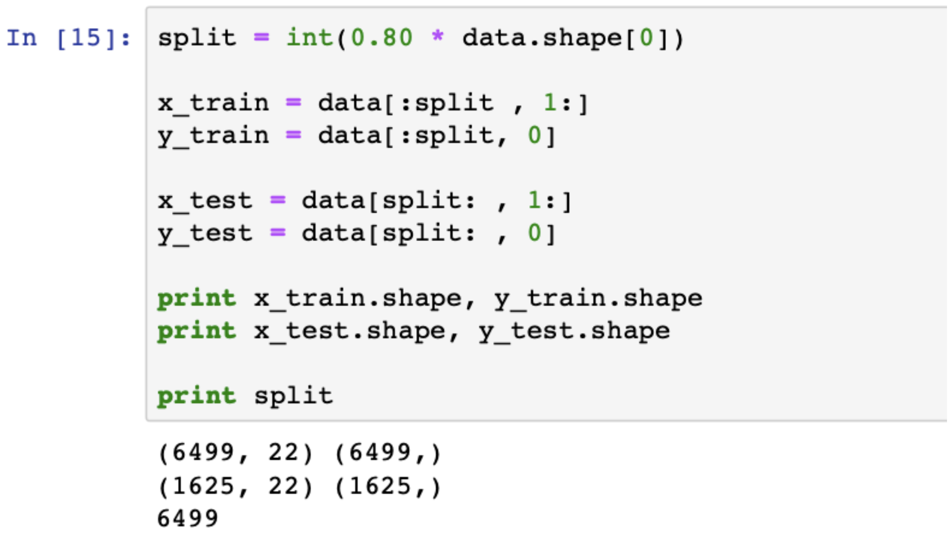


```
In [5]: y = np_utils.to_categorical(cate)
        Y_train = y[:split]
        Y_test = y[split:]

        print x_train.shape, x_test.shape
        print y_train.shape, y_test.shape
        print data.shape

(6499, 22) (1625, 22)
(6499,) (1625,)
(8124, 23)
```

Figure 4.1.2 convert train and test data sets into NumPy arrays

4.2 Data Splitting

The whole data set has been split into two sections which are training data set and testing data set. 80% of the whole data set which would be 6499, was taken to train the neural network. The rest which is 1625 was taken for testing the accuracy of the implemented model.

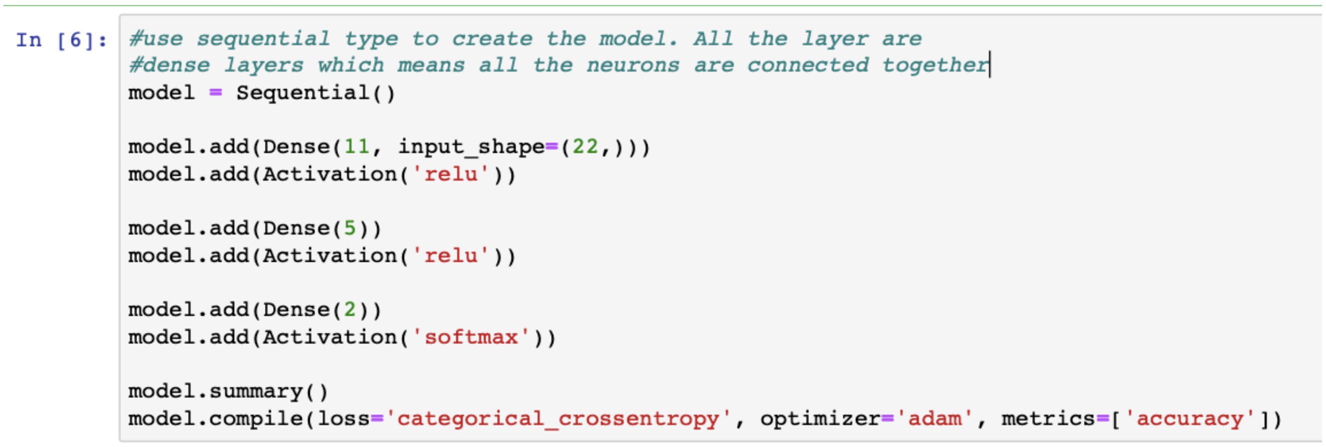


```
In [15]: split = int(0.80 * data.shape[0])

         x_train = data[:split , 1:]
         y_train = data[:split, 0]

         x_test = data[split: , 1:]
         y_test = data[split: , 0]

         print x_train.shape, y_train.shape
         print x_test.shape, y_test.shape

         print split

         (6499, 22) (6499,)
         (1625, 22) (1625,)
         6499
```

Figure 4.2.1 Data splitting

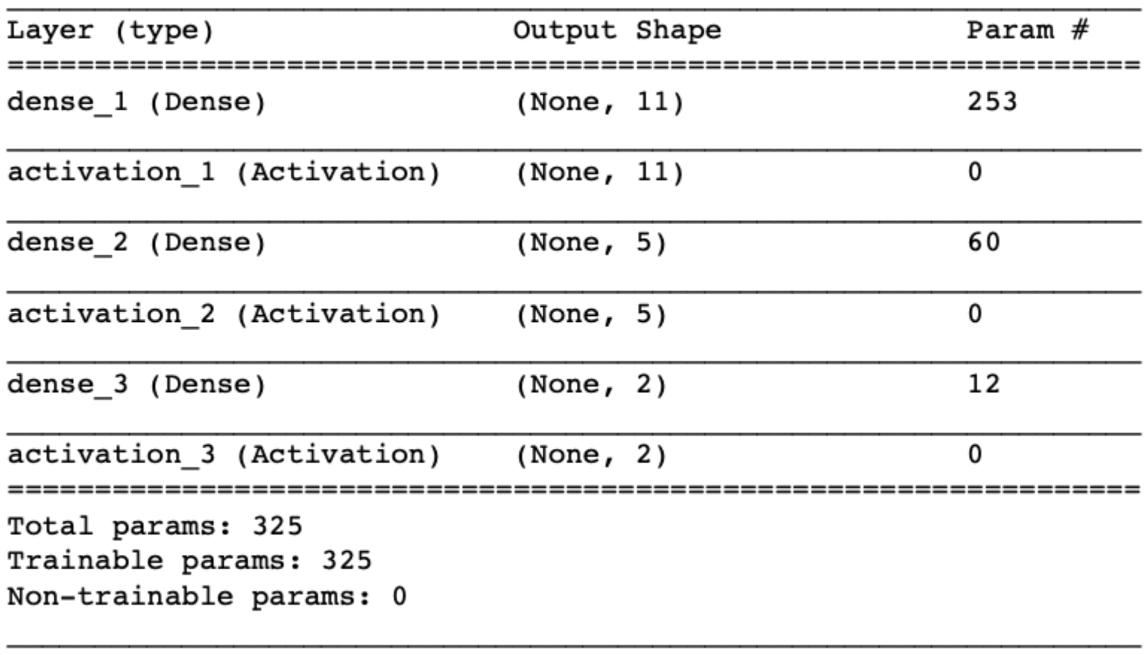
4.3 Model Creating

Next, I have come up with the designed neural network model using sequential model provided by Keras models.



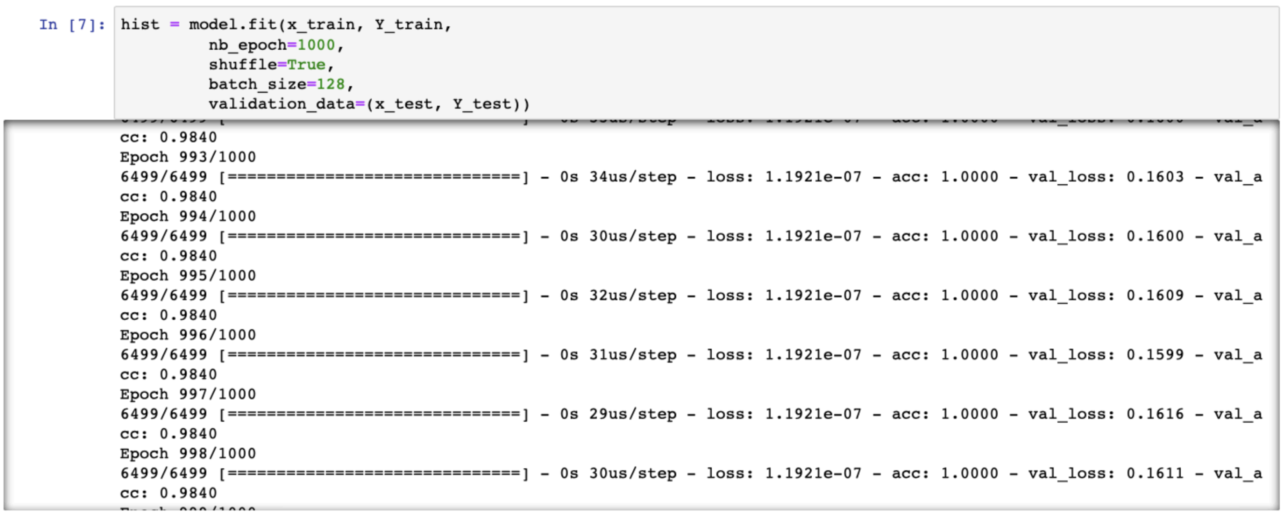
```
In [6]: #use sequential type to create the model. All the layer are
        #dense layers which means all the neurons are connected together
        model = Sequential()

        model.add(Dense(11, input_shape=(22,)))
        model.add(Activation('relu'))

        model.add(Dense(5))
        model.add(Activation('relu'))

        model.add(Dense(2))
        model.add(Activation('softmax'))

        model.summary()
        model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Feature 4.3.1 Model creation



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 11)                253       
_________________________________________________________________
activation_1 (Activation)    (None, 11)                0         
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 60        
_________________________________________________________________
activation_2 (Activation)    (None, 5)                 0         
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 12        
_________________________________________________________________
activation_3 (Activation)    (None, 2)                 0         
=================================================================
Total params: 325
Trainable params: 325
Non-trainable params: 0
_________________________________________________________________
```

Feature 4.3.2 Model Summary



```
In [7]: hist = model.fit(x_train, Y_train,
                 nb_epoch=1000,
                 shuffle=True,
                 batch_size=128,
                 validation_data=(x_test, Y_test))
```

```
cc: 0.9840
Epoch 993/1000
6499/6499 [==============================] - 0s 34us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1603 - val_a
cc: 0.9840
Epoch 994/1000
6499/6499 [==============================] - 0s 30us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1600 - val_a
cc: 0.9840
Epoch 995/1000
6499/6499 [==============================] - 0s 32us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1609 - val_a
cc: 0.9840
Epoch 996/1000
6499/6499 [==============================] - 0s 31us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1599 - val_a
cc: 0.9840
Epoch 997/1000
6499/6499 [==============================] - 0s 29us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1616 - val_a
cc: 0.9840
Epoch 998/1000
6499/6499 [==============================] - 0s 30us/step - loss: 1.1921e-07 - acc: 1.0000 - val_loss: 0.1611 - val_a
cc: 0.9840
```

Feature 4.3.4 Model fitting

Here I have used 1000 of epochs where one epoch would be to train the implemented model for all the instances/samples. By doing that I have tried to increase the accuracy level of my model. While training the model I have used. Following are the plot changes with respect to different optimizers in terms of accuracy and error loss.

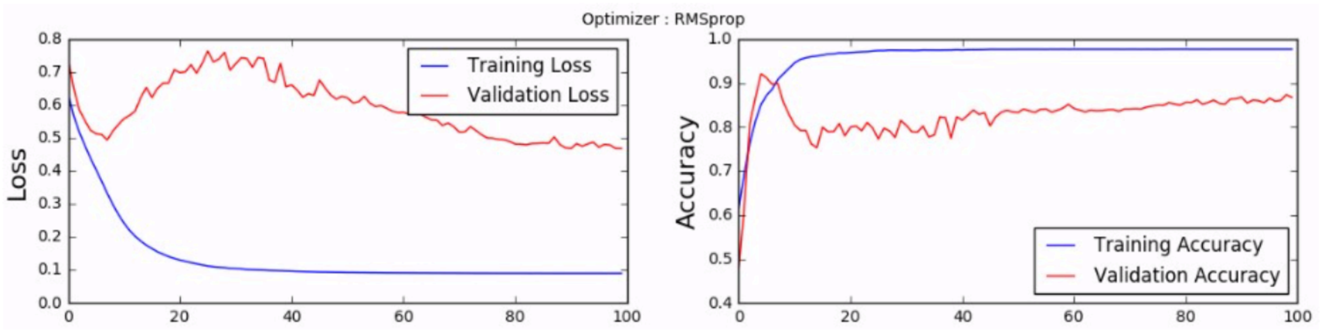


Figure 4.3.5 RMSprop optimizer

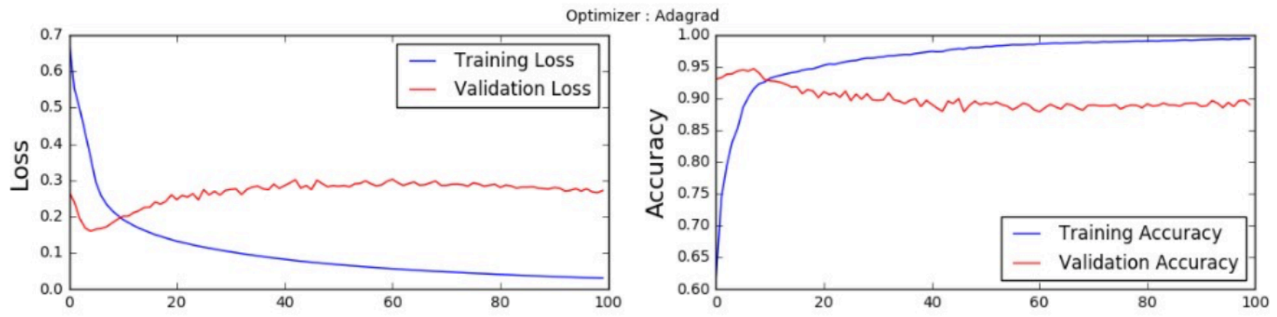


Figure 4.3.6 Adagrad optimizer

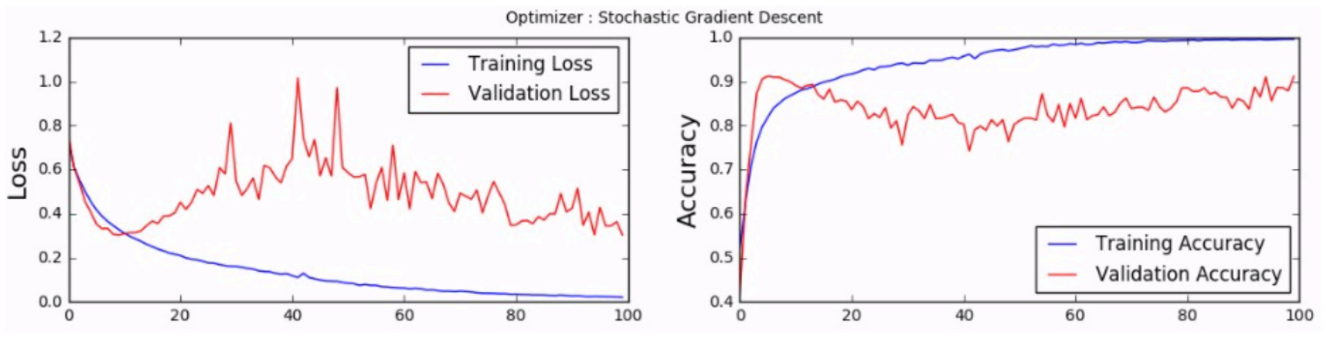


Figure 4.3.7 Gradient Descent Optimizer

5. Discussion

This feed forward neural network has proven approximately 97% accuracy level when classifying given dataset. The accuracy level could be increased by changing the model or by adding more neurons or by changing the number of hidden layers. The data set was gathered by examining 22 features of different types of mushrooms but I would suggest to come up with a simple convolutional neural network to classify the mushrooms via image processing (images of mushrooms) as feature work.

6. Appendix

```
import numpy as np
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.tree import DecisionTreeClassifier as DTC
from matplotlib import pyplot as plt
%matplotlib inline
import datetime
import pandas as pd
from sklearn import preprocessing as pp
from sklearn.linear_model import LogisticRegression as LR
from sklearn.neighbors import KNeighborsClassifier as KNN

import keras
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.utils import np_utils

ds = pd.read_csv('mushrooms.csv')
dat = ds.values

print dat.shape

headers = list(ds.columns.values) #store features of mushrooms
print(headers)
```

```
#Data Preprocessing
l = pp.LabelEncoder()
l.fit(dat[:, 0])
dataa = l.transform(dat[:, 0])

#come up with appropriate numerical data set
for ix in range(1, dat.shape[1]):
   le = pp.LabelEncoder()
   le.fit(dat[:, ix])
   y = le.transform(dat[:, ix])
   dataa = np.vstack((dataa , y))

data = dataa.T #tranpose the metrix

cate = data[:, 0] #One hot encoding for Neural Network
implementation. specify the targets.

print "data Dimenssion"
print data.shape

print "numerically converted data set"
print dataa

print "Expected targets, converted in to metrix format"
print cate

split = int(0.80 * data.shape[0])

x_train = data[:split , 1:]
y_train = data[:split, 0]

x_test = data[split: , 1:]
y_test = data[split: , 0]

print x_train.shape, y_train.shape
print x_test.shape, y_test.shape

print split

y = np_utils.to_categorical(cate)
Y_train = y[:split]
Y_test = y[split:]

print x_train.shape, x_test.shape
print y_train.shape, y_test.shape
print data.shape

#use sequential type to create the model. All the layer are
```

```
#dense layers which means all the neurons are connected
together
model = Sequential()


model.add(Dense(11, input_shape=(22,)))
model.add(Activation('relu'))


model.add(Dense(5))
model.add(Activation('relu'))


model.add(Dense(2))
model.add(Activation('softmax'))


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


hist = model.fit(x_train, Y_train,
        nb_epoch=1000,
        shuffle=True,
        batch_size=128,
        validation_data=(x_test, Y_test))


plt.figure(figsize=(14,3))
plt.subplot(1, 2, 1)
plt.suptitle('Optimizer : Adam', fontsize=10)
plt.ylabel('Loss', fontsize=16)
plt.plot(hist.history['loss'], 'b', label='Training Loss')
plt.plot(hist.history['val_loss'], 'r', label='Validation Loss')
plt.legend(loc='upper right')

plt.subplot(1, 2, 2)
plt.ylabel('Accuracy', fontsize=16)
plt.plot(hist.history['acc'], 'b', label='Training Accuracy')
plt.plot(hist.history['val_acc'], 'r', label='Validation Accuracy')
plt.legend(loc='lower right')
plt.show()
```