

In [1]:

```
import scipy.io as sio
import pandas as pd
import os
import numpy as np
import re
import keras
from keras.models import Model, Sequential
from keras.layers import Flatten, Dense, Input, Conv2D, MaxPooling2D, Dropout, Add, BatchNormalization, Conv1D, advanced_activations, UpSampling2D
from keras.callbacks import ModelCheckpoint
import matplotlib.pyplot as plt
from keras.optimizers import Adam, SGD
from sklearn.metrics import mean_absolute_error, classification_report, max_error, median_absolute_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
'''%load_ext tensorboard
import tensorflow as tf
import datetime, os'''
```

Using TensorFlow backend.

Out[1]:

```
'%load_ext tensorboard\nimport tensorflow as tf\nimport datetime, os'
```

Load and preprocess data

In [2]:

```
!unzip /content/85318_196940_bundle_archive.zip
inputData = pd.read_csv(r"/content/eeg_clean.csv");
#print(inputData.dtypes)
#print(inputData.columns)
#print("Data shape:",inputData.shape)
#print(inputData.head())
#print(inputData.describe())
#print(inputData.info())
# Check for any nulls
#print(inputData.isnull().sum())
inputData['eye']=inputData["eye"].astype('category')
inputData["eye"] = inputData["eye"].cat.codes

data=inputData.to_numpy()
temp=np.round(data[:,2])
data[:,2]=data[:,14]
data[:,14]=temp
dataC=data[data[:,14]==0,0:14]
dataO=data[data[:,14]==1,0:14]
dataC=np.transpose(dataC)
dataO=np.transpose(dataO)
print(np.shape(dataO))
print(np.shape(dataC))
dataOMat=np.zeros((114,14,1024))
dataCMat=np.zeros((87,14,1024))
count=0
for i in range(0,8257-1024,64):
    dataOMat[count,:,:]=(dataO[:,i:i+1024]-np.mean(dataO[:,i:i+1024]))/np.std(dataO[:,i:i+1024])
    count+=1
count=0
for i in range(0,6592-1024,64):
    dataCMat[count,:,:]=(dataC[:,i:i+1024]-np.mean(dataC[:,i:i+1024]))/np.std(dataC[:,i:i+1024])
    count+=1
#print(count)
print(np.shape(dataOMat))
print(np.shape(dataCMat))
dataX=np.append(dataOMat,dataCMat,axis=0)
dataY=np.append(np.ones(114),np.zeros(87))
dataX=np.reshape(dataX,(np.shape(dataX)[0],14,1024,1))
np.shape(dataX)
```

Archive: /content/85318_196940_bundle_archive.zip

inflating: eeg_clean.csv

(14, 8257)

(14, 6723)

(114, 14, 1024)

(87, 14, 1024)

Out[2]:

(201, 14, 1024, 1)

In [3]:

```
Input1=Input(shape=(14, 1024,1))
x=(Conv2D(filters=128, kernel_size=(3,3), padding='same'))(Input1) # input shape is the shape of one sample
x=(advanced_activations.LeakyReLU()(x))
x=(MaxPooling2D(pool_size=(1, 2), padding='same'))(x)

#model.add(Dropout(0.5))
x=(Conv2D(filters=64, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(MaxPooling2D(pool_size=(1, 2), padding='same'))(x)

#model.add(Dropout(0.5))
x=(Conv2D(filters=32, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(MaxPooling2D(pool_size=(1, 2), padding='same'))(x)

#model.add(Dropout(0.5))
x=(Conv2D(filters=8, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(MaxPooling2D(pool_size=(1, 2), padding='same'))(x)

x=(Conv2D(filters=2, kernel_size=(3,2), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
encoder=(MaxPooling2D(pool_size=(1, 2), padding='same'))(x)

x=(Conv2D(filters=2, kernel_size=(3,2), padding='same'))(encoder)
x=(advanced_activations.LeakyReLU()(x))
x=(UpSampling2D((1, 2)))(x)

x=(Conv2D(filters=8, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(UpSampling2D((1, 2)))(x)

x=(Conv2D(filters=32, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(UpSampling2D((1, 2)))(x)

x=(Conv2D(filters=64, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(UpSampling2D((1, 2)))(x)

x=(Conv2D(filters=128, kernel_size=(3,3), padding='same'))(x)
x=(advanced_activations.LeakyReLU()(x))
x=(UpSampling2D((1, 2)))(x)

decoder=(Conv2D(1, (3, 3), padding='same', activation='linear'))(x)

model=Model(inputs=Input1,outputs=decoder)
#model=Model(inputs=xInput,outputs=y)
# Compile the model
opt = SGD(lr=0.001, momentum=0.9) # Learning rate can be changed
model.compile(loss='mean_squared_error', optimizer= 'adam') # It is important to define metrics here to evaluate the model (see #4)
#binary_crossentropy, Adam(Lr=0.001)
model.summary()
```

Model: "model_1"

| Layer (type) | Output Shape | Param # |
|-------------------------------|-----------------------|---------|
| ===== | | |
| input_1 (InputLayer) | (None, 14, 1024, 1) | 0 |
| conv2d_1 (Conv2D) | (None, 14, 1024, 128) | 1280 |
| leaky_re_lu_1 (LeakyReLU) | (None, 14, 1024, 128) | 0 |
| max_pooling2d_1 (MaxPooling2) | (None, 14, 512, 128) | 0 |
| conv2d_2 (Conv2D) | (None, 14, 512, 64) | 73792 |
| leaky_re_lu_2 (LeakyReLU) | (None, 14, 512, 64) | 0 |
| max_pooling2d_2 (MaxPooling2) | (None, 14, 256, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 14, 256, 32) | 18464 |
| leaky_re_lu_3 (LeakyReLU) | (None, 14, 256, 32) | 0 |
| max_pooling2d_3 (MaxPooling2) | (None, 14, 128, 32) | 0 |
| conv2d_4 (Conv2D) | (None, 14, 128, 8) | 2312 |
| leaky_re_lu_4 (LeakyReLU) | (None, 14, 128, 8) | 0 |
| max_pooling2d_4 (MaxPooling2) | (None, 14, 64, 8) | 0 |
| conv2d_5 (Conv2D) | (None, 14, 64, 2) | 98 |
| leaky_re_lu_5 (LeakyReLU) | (None, 14, 64, 2) | 0 |
| max_pooling2d_5 (MaxPooling2) | (None, 14, 32, 2) | 0 |
| conv2d_6 (Conv2D) | (None, 14, 32, 2) | 26 |
| leaky_re_lu_6 (LeakyReLU) | (None, 14, 32, 2) | 0 |
| up_sampling2d_1 (UpSampling2) | (None, 14, 64, 2) | 0 |
| conv2d_7 (Conv2D) | (None, 14, 64, 8) | 152 |
| leaky_re_lu_7 (LeakyReLU) | (None, 14, 64, 8) | 0 |
| up_sampling2d_2 (UpSampling2) | (None, 14, 128, 8) | 0 |
| conv2d_8 (Conv2D) | (None, 14, 128, 32) | 2336 |
| leaky_re_lu_8 (LeakyReLU) | (None, 14, 128, 32) | 0 |
| up_sampling2d_3 (UpSampling2) | (None, 14, 256, 32) | 0 |
| conv2d_9 (Conv2D) | (None, 14, 256, 64) | 18496 |
| leaky_re_lu_9 (LeakyReLU) | (None, 14, 256, 64) | 0 |
| up_sampling2d_4 (UpSampling2) | (None, 14, 512, 64) | 0 |
| conv2d_10 (Conv2D) | (None, 14, 512, 128) | 73856 |

| | | |
|--------------------------------|-----------------------|------|
| leaky_re_lu_10 (LeakyReLU) | (None, 14, 512, 128) | 0 |
| up_sampling2d_5 (UpSampling2D) | (None, 14, 1024, 128) | 0 |
| conv2d_11 (Conv2D) | (None, 14, 1024, 1) | 1153 |
| ===== | | |
| Total params: 191,965 | | |
| Trainable params: 191,965 | | |
| Non-trainable params: 0 | | |

In [0]:

```
#train_x, test_x, train_y, test_y = train_test_split(dataX, dataY, test_size=0.05)
train_x, val_x, train_y, val_y = train_test_split(dataX, dataY, test_size=0.2)
```

In [0]:

```
model.load_weights('/content/Topology.hdf5')
```

In [5]:

```
# Checkpoint for saving the model

checkpointer = ModelCheckpoint(filepath='./weights.best.Autonnn.hdf5',
                               verbose = 0,
                               save_best_only = True) # verbose =1 is for printing the
output
# checkpointer is used for saving the

# Train the model

history=model.fit(train_x,train_x,
                  validation_data=(val_x, val_x),
                  batch_size = 1,
                  epochs = 100,
                  callbacks = [checkpointer],
                  verbose = 1) # verbose =1 is for printing the output, history stores
the history of training
'''
Logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = keras.callbacks.TensorBoard(logdir, histogram_freq=1)
history=model.fit(dataXR_train,dataY_train,
                  validation_split=0.2,
                  batch_size = 32,
                  epochs = 5,
                  callbacks=[tensorboard_callback],
                  verbose = 1) # verbose =1 is for printing the output, history stores the hist
ory of training

'''
#!cp /content/weights.best.CNNDep2.hdf5 "/content/drive/My Drive/Research/Depression/da
taCNN/" # save the weights to the drive
```

Train on 160 samples, validate on 41 samples

Epoch 1/100

160/160 [=====] - 6s 39ms/step - loss: 0.2290 - val_loss: 0.1208

Epoch 2/100

160/160 [=====] - 4s 26ms/step - loss: 0.1811 - val_loss: 0.1280

Epoch 3/100

160/160 [=====] - 4s 25ms/step - loss: 0.1730 - val_loss: 0.0981

Epoch 4/100

160/160 [=====] - 4s 25ms/step - loss: 0.1920 - val_loss: 0.0648

Epoch 5/100

160/160 [=====] - 4s 26ms/step - loss: 0.1569 - val_loss: 0.0798

Epoch 6/100

160/160 [=====] - 4s 26ms/step - loss: 0.1112 - val_loss: 0.0569

Epoch 7/100

160/160 [=====] - 4s 26ms/step - loss: 0.1028 - val_loss: 0.0449

Epoch 8/100

160/160 [=====] - 4s 26ms/step - loss: 0.0962 - val_loss: 0.0468

Epoch 9/100

160/160 [=====] - 4s 26ms/step - loss: 0.0891 - val_loss: 0.0490

Epoch 10/100

160/160 [=====] - 4s 26ms/step - loss: 0.0618 - val_loss: 0.0570

Epoch 11/100

160/160 [=====] - 4s 26ms/step - loss: 0.0955 - val_loss: 0.0436

Epoch 12/100

160/160 [=====] - 4s 25ms/step - loss: 0.0534 - val_loss: 0.0417

Epoch 13/100

160/160 [=====] - 4s 25ms/step - loss: 0.0467 - val_loss: 0.0413

Epoch 14/100

160/160 [=====] - 4s 26ms/step - loss: 0.0609 - val_loss: 0.0997

Epoch 15/100

160/160 [=====] - 4s 26ms/step - loss: 0.0617 - val_loss: 0.0442

Epoch 16/100

160/160 [=====] - 4s 25ms/step - loss: 0.0725 - val_loss: 0.0320

Epoch 17/100

160/160 [=====] - 4s 25ms/step - loss: 0.0435 - val_loss: 0.0403

Epoch 18/100

160/160 [=====] - 4s 25ms/step - loss: 0.0359 - val_loss: 0.0313

Epoch 19/100

160/160 [=====] - 4s 25ms/step - loss: 0.0338 - val_loss: 0.0217

Epoch 20/100

160/160 [=====] - 4s 25ms/step - loss: 0.0303 - val_loss: 0.0480

Epoch 21/100
160/160 [=====] - 4s 25ms/step - loss: 0.0664 - val_loss: 0.0313
Epoch 22/100
160/160 [=====] - 4s 25ms/step - loss: 0.0484 - val_loss: 0.0221
Epoch 23/100
160/160 [=====] - 4s 25ms/step - loss: 0.0210 - val_loss: 0.0163
Epoch 24/100
160/160 [=====] - 4s 26ms/step - loss: 0.0193 - val_loss: 0.0132
Epoch 25/100
160/160 [=====] - 4s 25ms/step - loss: 0.0201 - val_loss: 0.0170
Epoch 26/100
160/160 [=====] - 4s 26ms/step - loss: 0.0515 - val_loss: 0.0175
Epoch 27/100
160/160 [=====] - 4s 27ms/step - loss: 0.0220 - val_loss: 0.0261
Epoch 28/100
160/160 [=====] - 4s 27ms/step - loss: 0.0341 - val_loss: 0.0363
Epoch 29/100
160/160 [=====] - 4s 25ms/step - loss: 0.0294 - val_loss: 0.0226
Epoch 30/100
160/160 [=====] - 4s 25ms/step - loss: 0.0138 - val_loss: 0.0080
Epoch 31/100
160/160 [=====] - 4s 25ms/step - loss: 0.0116 - val_loss: 0.0108
Epoch 32/100
160/160 [=====] - 4s 25ms/step - loss: 0.0157 - val_loss: 0.0205
Epoch 33/100
160/160 [=====] - 4s 25ms/step - loss: 0.0350 - val_loss: 0.0240
Epoch 34/100
160/160 [=====] - 4s 25ms/step - loss: 0.1140 - val_loss: 0.0787
Epoch 35/100
160/160 [=====] - 4s 25ms/step - loss: 0.0493 - val_loss: 0.0124
Epoch 36/100
160/160 [=====] - 4s 25ms/step - loss: 0.0121 - val_loss: 0.0090
Epoch 37/100
160/160 [=====] - 4s 26ms/step - loss: 0.0107 - val_loss: 0.0081
Epoch 38/100
160/160 [=====] - 4s 25ms/step - loss: 0.0116 - val_loss: 0.0076
Epoch 39/100
160/160 [=====] - 4s 25ms/step - loss: 0.0092 - val_loss: 0.0072
Epoch 40/100
160/160 [=====] - 4s 26ms/step - loss: 0.0147 - val_loss: 0.0085
Epoch 41/100


```
160/160 [=====] - 4s 26ms/step - loss: 0.0270 - v
al_loss: 0.0240
Epoch 42/100
160/160 [=====] - 4s 26ms/step - loss: 0.0175 - v
al_loss: 0.0085
Epoch 43/100
160/160 [=====] - 4s 25ms/step - loss: 0.0131 - v
al_loss: 0.0110
Epoch 44/100
160/160 [=====] - 4s 26ms/step - loss: 0.0120 - v
al_loss: 0.0153
Epoch 45/100
160/160 [=====] - 4s 25ms/step - loss: 0.0123 - v
al_loss: 0.0085
Epoch 46/100
160/160 [=====] - 4s 26ms/step - loss: 0.0206 - v
al_loss: 0.0418
Epoch 47/100
160/160 [=====] - 4s 25ms/step - loss: 0.0349 - v
al_loss: 0.0101
Epoch 48/100
160/160 [=====] - 4s 25ms/step - loss: 0.0107 - v
al_loss: 0.0058
Epoch 49/100
160/160 [=====] - 4s 25ms/step - loss: 0.0084 - v
al_loss: 0.0077
Epoch 50/100
160/160 [=====] - 4s 25ms/step - loss: 0.0304 - v
al_loss: 0.0383
Epoch 51/100
160/160 [=====] - 4s 26ms/step - loss: 0.0201 - v
al_loss: 0.0070
Epoch 52/100
160/160 [=====] - 4s 26ms/step - loss: 0.0134 - v
al_loss: 0.0106
Epoch 53/100
160/160 [=====] - 4s 26ms/step - loss: 0.0124 - v
al_loss: 0.0091
Epoch 54/100
160/160 [=====] - 4s 26ms/step - loss: 0.0087 - v
al_loss: 0.0053
Epoch 55/100
160/160 [=====] - 4s 26ms/step - loss: 0.0093 - v
al_loss: 0.0077
Epoch 56/100
160/160 [=====] - 4s 26ms/step - loss: 0.0152 - v
al_loss: 0.0291
Epoch 57/100
160/160 [=====] - 4s 26ms/step - loss: 0.0234 - v
al_loss: 0.0084
Epoch 58/100
160/160 [=====] - 4s 25ms/step - loss: 0.0217 - v
al_loss: 0.0504
Epoch 59/100
160/160 [=====] - 4s 25ms/step - loss: 0.0206 - v
al_loss: 0.0133
Epoch 60/100
160/160 [=====] - 4s 25ms/step - loss: 0.0138 - v
al_loss: 0.0154
Epoch 61/100
160/160 [=====] - 4s 26ms/step - loss: 0.0161 - v
```

```
al_loss: 0.0079
Epoch 62/100
160/160 [=====] - 4s 25ms/step - loss: 0.0165 - v
al_loss: 0.0297
Epoch 63/100
160/160 [=====] - 4s 26ms/step - loss: 0.0113 - v
al_loss: 0.0056
Epoch 64/100
160/160 [=====] - 4s 25ms/step - loss: 0.0108 - v
al_loss: 0.0299
Epoch 65/100
160/160 [=====] - 4s 25ms/step - loss: 0.0136 - v
al_loss: 0.0081
Epoch 66/100
160/160 [=====] - 4s 25ms/step - loss: 0.0195 - v
al_loss: 0.0062
Epoch 67/100
160/160 [=====] - 4s 25ms/step - loss: 0.0264 - v
al_loss: 0.0112
Epoch 68/100
160/160 [=====] - 4s 25ms/step - loss: 0.0079 - v
al_loss: 0.0082
Epoch 69/100
160/160 [=====] - 4s 25ms/step - loss: 0.0121 - v
al_loss: 0.0088
Epoch 70/100
160/160 [=====] - 4s 25ms/step - loss: 0.0134 - v
al_loss: 0.0265
Epoch 71/100
160/160 [=====] - 4s 26ms/step - loss: 0.0110 - v
al_loss: 0.0079
Epoch 72/100
160/160 [=====] - 4s 25ms/step - loss: 0.0108 - v
al_loss: 0.0078
Epoch 73/100
160/160 [=====] - 5s 28ms/step - loss: 0.0107 - v
al_loss: 0.0141
Epoch 74/100
160/160 [=====] - 4s 28ms/step - loss: 0.0098 - v
al_loss: 0.0077
Epoch 75/100
160/160 [=====] - 4s 27ms/step - loss: 0.0130 - v
al_loss: 0.0269
Epoch 76/100
160/160 [=====] - 4s 25ms/step - loss: 0.0242 - v
al_loss: 0.0540
Epoch 77/100
160/160 [=====] - 4s 25ms/step - loss: 0.0947 - v
al_loss: 0.0363
Epoch 78/100
160/160 [=====] - 4s 25ms/step - loss: 0.0125 - v
al_loss: 0.0090
Epoch 79/100
160/160 [=====] - 4s 25ms/step - loss: 0.0111 - v
al_loss: 0.0073
Epoch 80/100
160/160 [=====] - 4s 25ms/step - loss: 0.0109 - v
al_loss: 0.0103
Epoch 81/100
160/160 [=====] - 4s 25ms/step - loss: 0.0161 - v
al_loss: 0.0071
```

Epoch 82/100
160/160 [=====] - 4s 25ms/step - loss: 0.0165 - val_loss: 0.0045
Epoch 83/100
160/160 [=====] - 4s 25ms/step - loss: 0.0054 - val_loss: 0.0063
Epoch 84/100
160/160 [=====] - 4s 26ms/step - loss: 0.0062 - val_loss: 0.0046
Epoch 85/100
160/160 [=====] - 4s 25ms/step - loss: 0.0051 - val_loss: 0.0043
Epoch 86/100
160/160 [=====] - 4s 26ms/step - loss: 0.0094 - val_loss: 0.0069
Epoch 87/100
160/160 [=====] - 4s 26ms/step - loss: 0.0074 - val_loss: 0.0056
Epoch 88/100
160/160 [=====] - 4s 26ms/step - loss: 0.0118 - val_loss: 0.0056
Epoch 89/100
160/160 [=====] - 4s 25ms/step - loss: 0.0110 - val_loss: 0.0118
Epoch 90/100
160/160 [=====] - 4s 25ms/step - loss: 0.0203 - val_loss: 0.0053
Epoch 91/100
160/160 [=====] - 4s 25ms/step - loss: 0.0114 - val_loss: 0.0103
Epoch 92/100
160/160 [=====] - 4s 25ms/step - loss: 0.0159 - val_loss: 0.0074
Epoch 93/100
160/160 [=====] - 4s 25ms/step - loss: 0.0066 - val_loss: 0.0101
Epoch 94/100
160/160 [=====] - 4s 25ms/step - loss: 0.0097 - val_loss: 0.0085
Epoch 95/100
160/160 [=====] - 4s 25ms/step - loss: 0.0106 - val_loss: 0.0218
Epoch 96/100
160/160 [=====] - 4s 26ms/step - loss: 0.0339 - val_loss: 0.0191
Epoch 97/100
160/160 [=====] - 4s 26ms/step - loss: 0.0412 - val_loss: 0.0288
Epoch 98/100
160/160 [=====] - 4s 25ms/step - loss: 0.0360 - val_loss: 0.0070
Epoch 99/100
160/160 [=====] - 4s 26ms/step - loss: 0.0099 - val_loss: 0.0059
Epoch 100/100
160/160 [=====] - 4s 25ms/step - loss: 0.0063 - val_loss: 0.0064

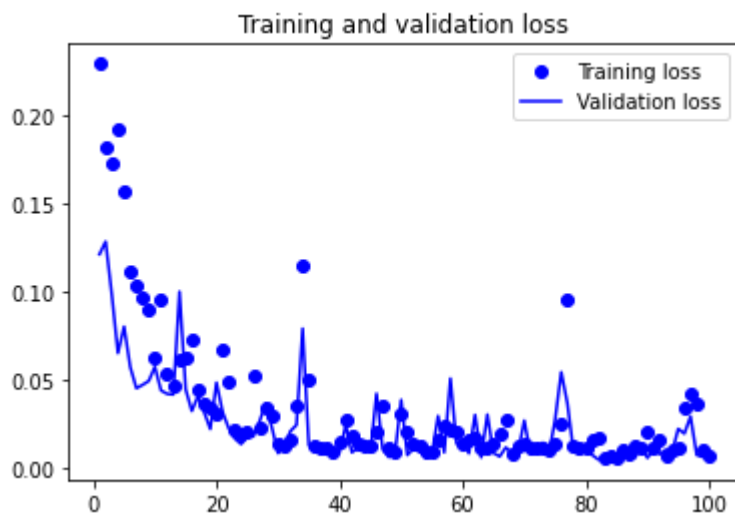
Out[5]:

```
' \nlogdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%
m%d-%H%M%S"))\ntensorboard_callback = keras.callbacks.TensorBoard(logdir,
histogram_freq=1)\nhistory=model.fit(dataXR_train,dataY_train,\n
validation_split=0.2,\n          batch_size = 32,\n          epochs = 5,\ncallbacks=[tensorboard_callback], \n          verbose = 1) # verbose =1 is
for printing the output, history stores the history of training\n
\n'
```

In [6]:

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```



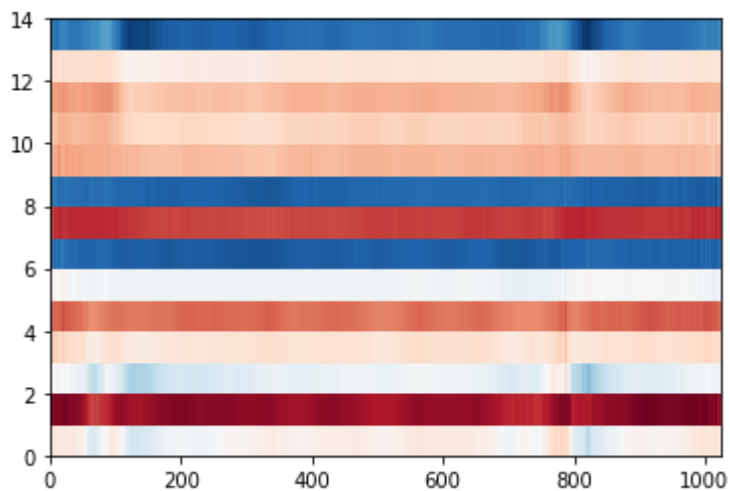
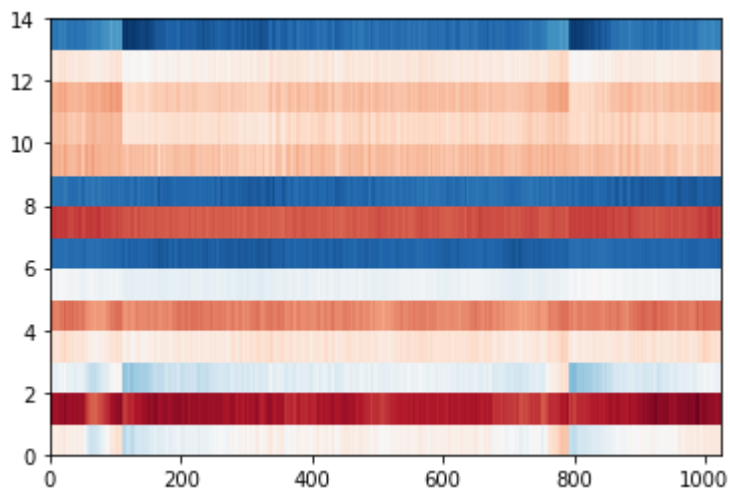
In [7]:

```
decoded_imgs = model.predict(dataX[150:150+2,:,:,:])

cmap = plt.get_cmap('RdBu')
n = 1
plt.figure(figsize=(20, 4))
for i in range(1,n+1):
    # display original
    #ax = plt.subplot(2, n, i)
    plt.figure()
    plt.pcolormesh(dataX[150:150+2,:,:,:][i].reshape(14,1024),cmap=cmap)
    #plt.gray()
    #ax.get_xaxis().set_visible(False)
    #ax.get_yaxis().set_visible(False)
    plt.figure()

    #ax = plt.subplot(2, n, i + n)
    plt.pcolormesh(decoded_imgs[i].reshape(14,1024),cmap=cmap)
    #plt.gray()
    #ax.get_xaxis().set_visible(False)
    #ax.get_yaxis().set_visible(False)
plt.show()
```

<Figure size 1440x288 with 0 Axes>



In [8]:

```
model2=Model(inputs=model.input,outputs=encoder)
model2.summary()
```

Model: "model_2"

| Layer (type) | Output Shape | Param # |
|------------------------------|-----------------------|---------|
| ===== | | |
| input_1 (InputLayer) | (None, 14, 1024, 1) | 0 |
| conv2d_1 (Conv2D) | (None, 14, 1024, 128) | 1280 |
| leaky_re_lu_1 (LeakyReLU) | (None, 14, 1024, 128) | 0 |
| max_pooling2d_1 (MaxPooling2 | (None, 14, 512, 128) | 0 |
| conv2d_2 (Conv2D) | (None, 14, 512, 64) | 73792 |
| leaky_re_lu_2 (LeakyReLU) | (None, 14, 512, 64) | 0 |
| max_pooling2d_2 (MaxPooling2 | (None, 14, 256, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 14, 256, 32) | 18464 |
| leaky_re_lu_3 (LeakyReLU) | (None, 14, 256, 32) | 0 |
| max_pooling2d_3 (MaxPooling2 | (None, 14, 128, 32) | 0 |
| conv2d_4 (Conv2D) | (None, 14, 128, 8) | 2312 |
| leaky_re_lu_4 (LeakyReLU) | (None, 14, 128, 8) | 0 |
| max_pooling2d_4 (MaxPooling2 | (None, 14, 64, 8) | 0 |
| conv2d_5 (Conv2D) | (None, 14, 64, 2) | 98 |
| leaky_re_lu_5 (LeakyReLU) | (None, 14, 64, 2) | 0 |
| max_pooling2d_5 (MaxPooling2 | (None, 14, 32, 2) | 0 |
| ===== | | |
| Total params: 95,946 | | |
| Trainable params: 95,946 | | |
| Non-trainable params: 0 | | |

In [10]:

```
sizedata=201
decoded_imgs = model2.predict(dataX[0:sizedata,:,:,])
print(np.shape(decoded_imgs))
print(decoded_imgs[0,0,0:5,0])
new=np.reshape(decoded_imgs,(sizedata,14*32*2))

print(np.shape(new))
print(new[0,0:5])
new = StandardScaler().fit_transform(new) # normalizing the features

new[dataY[0:sizedata]==1,:]=new[dataY[0:sizedata]==1,:]+1
pca_new = PCA(n_components=2)
new_pca = pca_new.fit_transform(new)
print(np.shape(new_pca))
new_pca_Df = pd.DataFrame(data = new_pca, columns = ['principal component 1', 'principal component 2'])
print('Explained variation per principal component: {}'.format(pca_new.explained_variance_ratio_))
plt.figure()
plt.figure(figsize=(10,10))
plt.xticks(fontsize=12)
plt.yticks(fontsize=14)
plt.xlabel('Principal Component - 1',fontsize=20)
plt.ylabel('Principal Component - 2',fontsize=20)
plt.title("Principal Component Analysis of Eye state Dataset",fontsize=20)
targets = [0,1]
colors = ['r', 'g']
for target, color in zip(targets,colors):
    indicesToKeep = dataY[0:sizedata] == target
    plt.scatter(new_pca_Df.loc[indicesToKeep, 'principal component 1'],
                new_pca_Df.loc[indicesToKeep, 'principal component 2'], c = color, s =
50)

plt.legend(targets,prop={'size': 15})
```

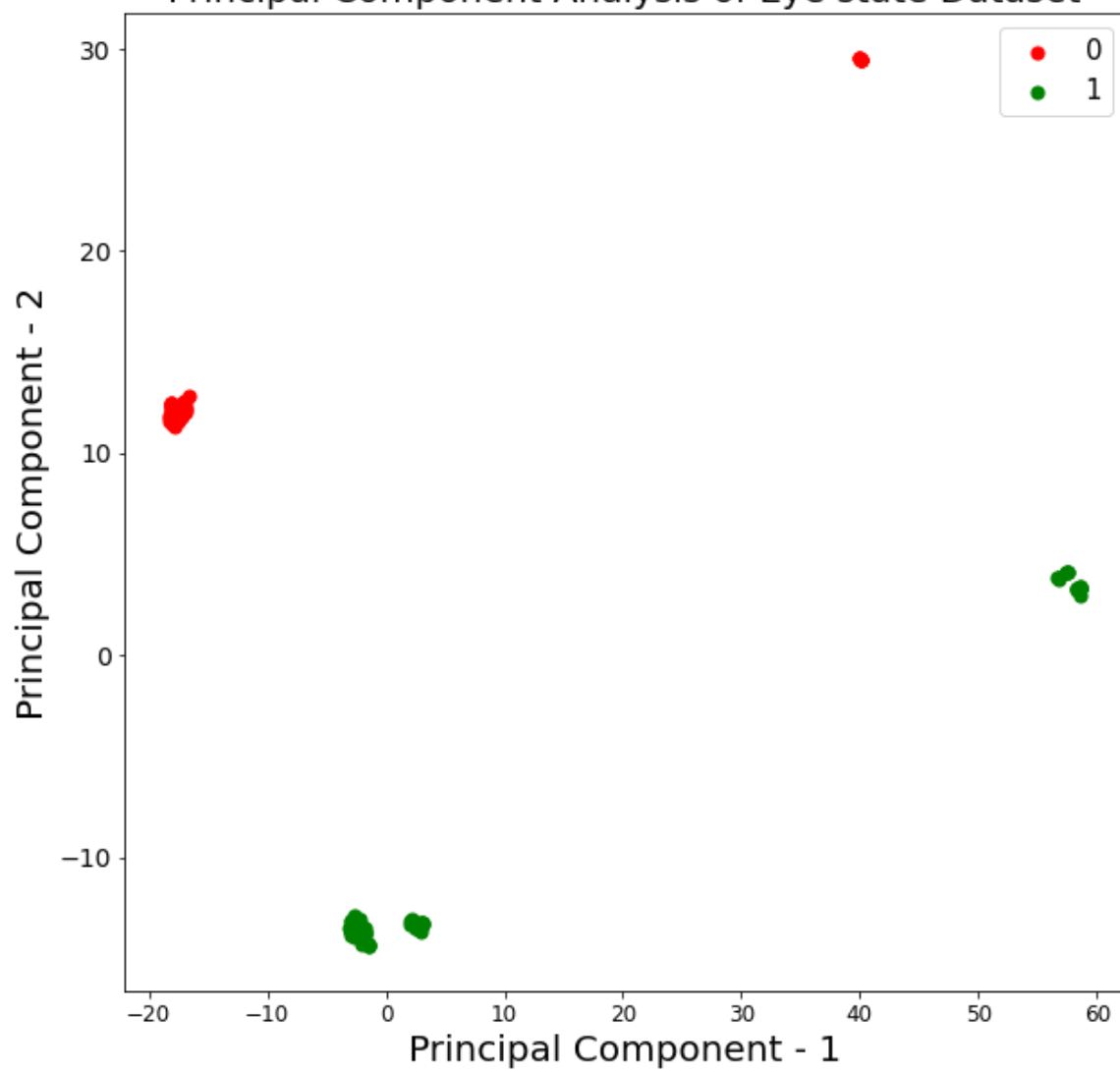
```
(201, 14, 32, 2)
[0.15545732 0.15513527 0.15472338 0.15323478 0.17778614]
(201, 896)
[ 0.15545732 -0.10791297  0.15513527 -0.10782877  0.15472338]
(201, 2)
Explained variation per principal component: [0.46661112 0.16091318]
```

Out[10]:

<matplotlib.legend.Legend at 0x7f90d034aef0>

<Figure size 432x288 with 0 Axes>

Principal Component Analysis of Eye state Dataset



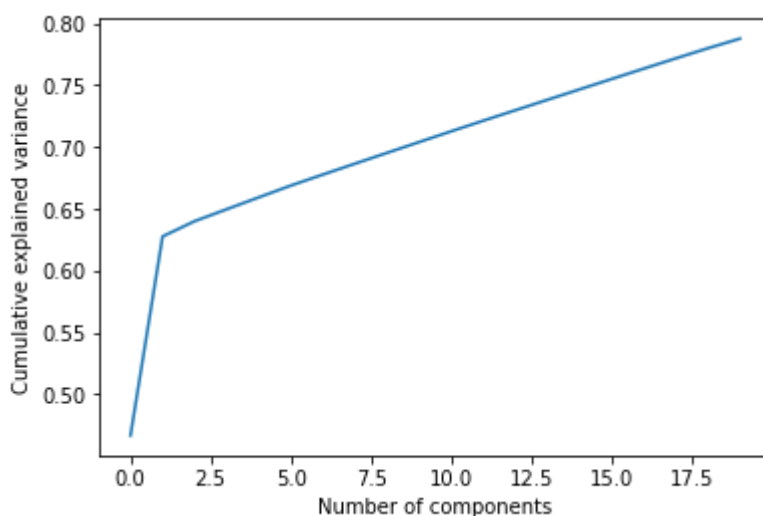
In [11]:

```
pca_new = PCA(n_components=20)
new_pca2 = pca_new.fit_transform(new)
print(np.shape(new_pca2))
print(pca_new.explained_variance_ratio_)
plt.plot(np.cumsum(pca_new.explained_variance_ratio_))
plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')
```

```
(201, 20)
[0.46661112 0.16091323 0.01235367 0.00964293 0.00962654 0.00953972
 0.00890248 0.00879472 0.00875589 0.00873628 0.00870316 0.0085782
 0.00845612 0.00843674 0.00841596 0.00838874 0.0083763 0.0083146
 0.00817322 0.00777856]
```

Out[11]:

```
Text(0, 0.5, 'Cumulative explained variance')
```



In [12]:

```
from sklearn.cluster import KMeans
clusters = 4

kmeans = KMeans(n_clusters = clusters)
kmeans.fit(new)
print(kmeans.labels_)
```

[illegible]

In [23]:

```
finalPrediction=((kmeans.labels_==1)+(kmeans.labels_==3)).astype(int)
print(finalPrediction)
print((dataY).astype(int))
print("Accuracy: ",sum(finalPrediction==(dataY).astype(int))*100/201,"%")
```

Accuracy: 100.0 %

In [0]:

```
model.save('/content/Topology.h5')  
model.save_weights('/content/Topology.hdf5')
```