Neural Computing and Deep Learning

Module Code: MOD006568
Academic Year: 2021 - 2022
SID: 2050132
Trimester: 2

Table Of Contents:

Background & Description

Recent research (Intel & MobileODT Cervical Cancer Screening | Kaggle, 2017) has shown that women can get access to life saving medication much closer to their location of domicile. After years of research, it has come to light that cervical cancer can be cured if it is taken care of in its nascent stages. The greatest hindrance to women getting exemplar services is the lack of talented personnel. Healthcare workers are much concerned about women from rural villages who might not be able to avail the treatment on the basis of the location of their cervix. That too, they cannot prescribe the same method of treatment to all the women as it will lead to a lot of complications as a result of incompatibility or as they say one man's medicine is another man's poison. At the moment, MobileODT provides a "Quality Assurance workflow" which enables healthcare workers to provide good healthcare to the rural populace.

Data Analysis & Data Pre-processing

Intel & MobileODT Cervical Cancer Screening

A Custom CNN using Keras over Tensorflow has been created. The data has been extracted into a numpy file.

```
In [1]: pip install piexif
```

```
Requirement already satisfied: piexif in c:\anaconda\lib\site-packages (1.1.3)
Note: you may need to restart the kernel to use updated packages.
```

```
WARNING: You are using pip version 21.3.1; however, version 22.0.4 is available.
You should consider upgrading via the 'C:\Anaconda\python.exe -m pip install --upgrade pip' command.
```

The installation of piexif in this python script using the pip command would enable me to include tools necessary for creation, extraction, manipulation, conversion and writing of data to JPEG, TIFF files, etc.

```
In [2]: import os
        import piexif
        import cv2
        import numpy as np
        from sklearn.model_selection import train_test_split
        import sys
```

```
In [3]: #Images are going to be square so set size to 32 to be used for both width and height.
        img_size = 32
        train_dir = r"C:\Users\Dwayne D'costa\Documents\Anglia Ruskin University\Tutorials\Neural Computing and Deep Learning\Cervical_Ca
        test_dir = r"C:\Users\Dwayne D'costa\Documents\Anglia Ruskin University\Tutorials\Neural Computing and Deep Learning\Cervical_Car
```

The image above depicts the libraries that have been imported in order to enable this code to run seamlessly. It also specifies the size of the image which has been set as well as the file paths of the train and test directories respectively.

In [4]:
```
def PreProcess_Images(root, train=True):
    features = []
    labels = []

    for subdir, dirs, files in os.walk(root):
        count  = 0
        for file in files:
            tot_files = len(files)
            if not file == ".DS_Store":
                count += 1
                sys.stdout.write("\rFile = " + file + " ----- Progress: {:2.1f}%".format(100 * count/float(tot_files)))
                img = os.path.join(subdir, file)
                #Remove exif data - This is because there is a lot of corrupt exif data in this dataset.
                if os.stat(img).st_size > 0:
                    piexif.remove(img)
                else:
                    continue
                #Open image and resize to designated width and height.
                im = cv2.imread(img)
                im = cv2.resize(im, (img_size, img_size))
                #Extract features into a numpy array.
                feature = np.array(im, dtype=np.float32)
                #append feature to features list.
                features.append(feature)

                #only apply labels for training data.
                if train == True:
                    #Get label from directory name.
                    label = os.path.basename(subdir)
                    #One hot encoding of label names.
                    if label == "1":
                        label = [1,0,0]
```

The images get resized in the cell above, so do features get extracted into the numpy array.

```
                    elif label == "2":
                        label = [0,1,0]
                    else:
                        label = [0,0,1]
                    #append label to labels list.
                    labels.append(label)
                #add image filename to labels to be used in formatting of submission data.
                else:
                    label = os.path.basename(img)
                    labels.append(label)
                sys.stdout.flush()

    if train == True:
        labels = np.array(labels, np.uint8)

    features = np.array(features, np.float32) / 255.

    return features, labels
```

```
# Obtain Training X and y lists.
X, y = PreProcess_Images(train_dir, train=True)
```

```
File = 996.jpg ----- Progress: 100.0%
```

```
# Obtain test X and filenames of test images
X_test, flnm_test = PreProcess_Images(test_dir, train=False)
```

```
File = 99.jpg ----- Progress: 100.0%
```

The X and Y train and tests lists have their images preprocessed in the above image.

In [7]:
```
#Split training data into training and validation data.
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.20, random_state=42)
```

In [8]:
```
#Save all information to a numpy archive file to be used when training the model.
np.savez('data_arrays', X_train, y_train, X_valid, y_valid, X_test, flnm_test)
```

In [9]:
```
import numpy as np
import keras as k
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D, ZeroPadding2D
from keras import optimizers
import matplotlib.pyplot as plt
import pandas as pd
import tensorflow as tf

from tensorflow import keras
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.callbacks import Callback
from keras import regularizers
from keras import optimizers
```

The dataset gets split into training data and validation data, after which all the information is saved into a numy file archive so that it can be used for training the model.

In [10]:
```
def SummaryGraphs(hist):
    # summarize history for accuracy
    plt.plot(hist.history['accuracy'])
    plt.plot(hist.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'valid'], loc='upper left')
    plt.show()
    # summarize history for loss
    plt.plot(hist.history['loss'])
    plt.plot(hist.history['val_loss'])
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'valid'], loc='upper left')
    plt.show()
```

Here, the values concerning the accuracy and loss in the histogram are being tallied.

In [11]:
```
def QuickModel(learning_rate, opt_momentum, opt_decay, dropout):
    #Quick Keras Model
    model = Sequential()
    model.add(ZeroPadding2D((1,1),input_shape=(32,32,3)))
    model.add(Conv2D(32, (3, 3),activation='relu'))
    model.add(Dropout(dropout))
    model.add(Conv2D(32, (3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=None, padding='valid', data_format=None))
    model.add(Dropout(dropout))
    model.add(Conv2D(128, (3, 3), activation='relu'))
    model.add(Flatten())
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(dropout))
    model.add(Dense(3, activation='softmax'))
    model.compile(loss='categorical_crossentropy',
                  optimizer=optimizers.SGD(lr=learning_rate, momentum=opt_momentum, decay=opt_decay),
                  metrics=['accuracy']
                 )
    return model
```

In [12]:
```
def Train(learning_rate, momentum, decay, dropout, epochs, batch_size, slice_size, xtrain, ytrain, xval, yval, logging=0, graph=
    #Model
    model = QuickModel(learning_rate, momentum, decay, dropout)

    #Fit Model and save results to history for graphing later.
    history = model.fit(xtrain[:slice_size], ytrain[:slice_size],
              batch_size=batch_size,
              epochs=epochs,
              verbose=logging,
              validation_data=(xval[:slice_size], yval[:slice_size]))
    if graph == True:
        SummaryGraphs(history)
    return model
```

In the image, the Keras model and fit models have been initiated for plotting in the histogram at a later date.

In [13]:
```
#Extract Data for training and testing from the .npz file.
with np.load('data_arrays.npz') as data:
    xtr = data['arr_0']
    ytr = data['arr_1']
    xvl = data['arr_2']
    yvl = data['arr_3']
    xts = data['arr_4']
    yts = data['arr_5']
```

Sanity Checks

Reference: CS231

1) Look for correct loss at chance performance.

- Diffuse Probability = 0.33 for each class (3 classes).
- Softmax => -ln(correct class) = -ln(0.33) = 1.10866 => Estimated Loss at start of training.
- Set Regularization(dropout) to zero.
- Initialize hyperparameters as small values.

In [14]:
```
from tensorflow.keras import optimizers

Train(learning_rate=0.0, momentum=0.0, decay=0.0, dropout=0.0, epochs=1,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=1)
```

```
C:\Users\Dwayne D'costa\AppData\Roaming\Python\Python38\site-packages\keras\optimizer_v2\gradient_descent.py:102: UserWarning:
The `lr` argument is deprecated, use `learning_rate` instead.
  super(SGD, self).__init__(name, **kwargs)
```

```
10/10 [==============================] - 2s 116ms/step - loss: 1.1202 - accuracy: 0.0633 - val_loss: 1.1195 - val_accuracy: 0.0
539
```

The above image depicts the extraction of data for training and testing from the .npz files. It also includes a soft max activation function.

- As we can see the initial model training loss is pretty close to what we expect.

2) As a second sanity check, increasing the regularization strength should increase the loss.

- The dropouut rate will be increased which means we should see the loss increase from above.

In [15]:
```
Train(learning_rate=0.0, momentum=0.0, decay=0.0, dropout=0.5, epochs=1,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=1)
```

```
10/10 [==============================] - 2s 158ms/step - loss: 1.2390 - accuracy: 0.1478 - val_loss: 1.1313 - val_accuracy: 0.0
034
```

Out[15]:
```
<keras.engine.sequential.Sequential at 0x29b4fc5fc40>
```

- We can see that the training loss increased from 1.1186 to 1.1313 with a dropout of 0.5

3) Overfit a tiny subset of data.

- If I can't reach a loss of zero, then there is a problem.
- Set the regularization(dropout) to zero.

In [16]:
```
Train(learning_rate=0.01, momentum=0.0, decay=0.0, dropout=0.0, epochs=300,
      batch_size=128, slice_size=10, xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=0, graph=True)
```

model accuracy

This image depicts an increase in the drop out rate as well as the overfitting of the following subset.

- As we can see in the "model loss" graph, the training loss has gone to zero. Thus, I was able to overfit the model with a small subset of the data.

Training

- I will now begin to experiment with hyperparameters during training to determine the best solution for this particular model.

In [17]:
```
model = Train(learning_rate=0.01, momentum=0.0, decay=0.0, dropout=0.5, epochs=50,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=0, graph=True)
```

This image signals the beginning of the training of the dataset.

It looks like we still have some to gain from this model. I'm going to leave everything the same except for learning rate and see how it performs. I will increase the learning rate.

In [18]:
```
model = Train(learning_rate=0.05, momentum=0.0, decay=0.0, dropout=0.5, epochs=50,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=0, graph=True)
```

This cell focuses towards increasing the learning rate.

epoch

The validation and training accuracy started to drift apart just after 30 epochs. So I'm going to decrease the learning rate back down to 0.01 increase the epochs and give it a little bit of momentum.

In [19]:
```
model = Train(learning_rate=0.01, momentum=0.01, decay=0.0, dropout=0.5, epochs=75,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=0, graph=True)
```

In the above image shows that the validation and training accuracy start to drift apart.

After playing around with hyperparameters I have settled on this model for now.

In [20]:
```
model = Train(learning_rate=0.01, momentum=0.01, decay=0.0, dropout=0.5, epochs=115,
      batch_size=128, slice_size=len(xtr), xtrain=xtr, ytrain=ytr, xval=xvl, yval=yvl, logging=0, graph=True)
```

The resulting graphs pertaining to the above code are model accuracy by accuracy and model loss by loss respectively.

Below I will create a submission and submit it to Kaggle for official scoring.

In [22]:
```
def Submission(mod, img_names, test_imgs):
    #Create Prediction File(.csv)
    test_predictions = mod.predict(test_imgs, batch_size=32, verbose=0)
    test_data = np.column_stack((img_names,test_predictions))
    dfPreds = pd.DataFrame(data=test_data,columns=['image_name','Type_1','Type_2','Type_3'])
    dfPreds.to_csv('submission_1.csv', index=False)
```

In [23]:
```
Submission(model, yts, xts)
```

This model had a logloss of 0.91613 on the test data in the Kaggle submission.

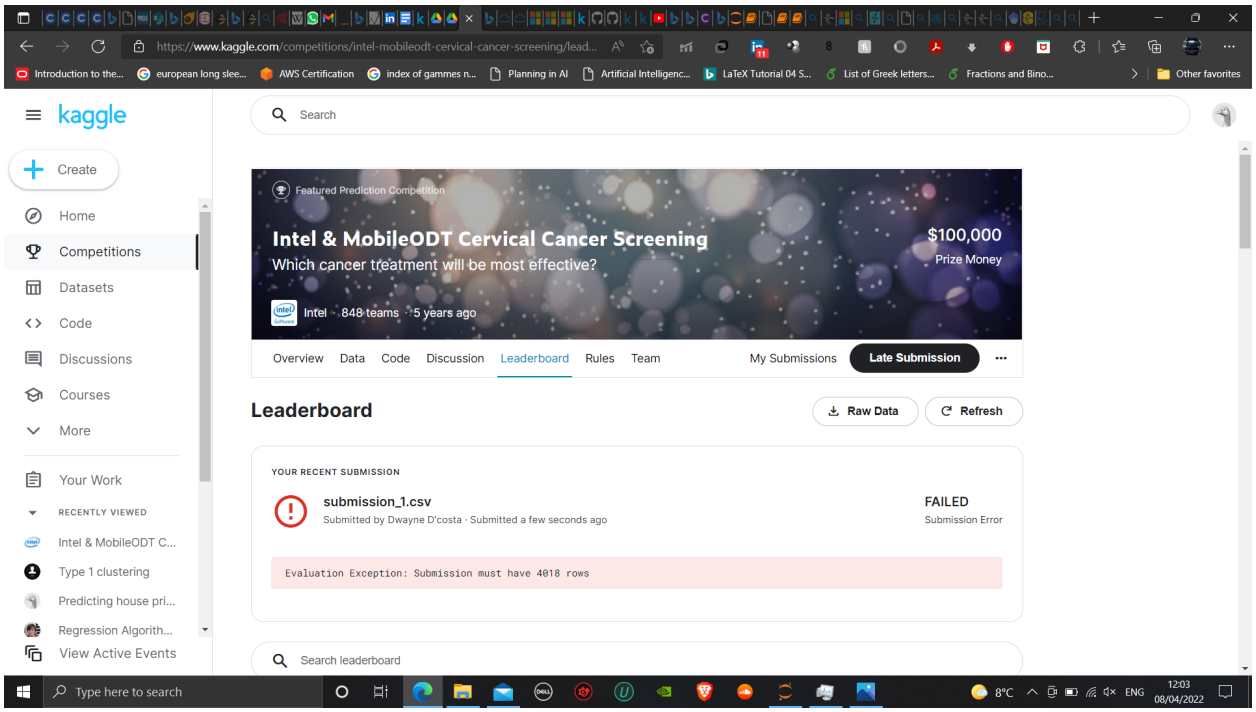
Finally the submission file has been created.

Critical Analysis

According to this article(Lin, RoyChowdhury and Maji, 2022) a proposal is made for bilinear models which is a type of recognition based architecture and consists of a couple of feature extractors whose results “are multiplied using outer product at each location of the image” and then accumulated together. The extractors in the bilinear models are based upon convoluted neural networks. This further simplifies gradient based computing and approves of an end-to-end training of both networks utilising image-labels. After training and testing, results depict that the proposed architecture is compared favourably with respect to state-of-the-art existing fine-grained datasets.

According to this paper (Sharma, Berwal and Ghai, 2020) states that segmented data is used to train a convolutional neural network model. S-CNN models training with segmented images as compared to their F-CNN counterparts have a 98.6% accuracy if it is tested on a new dataset that hasn't been introduced before. They thus help in bringing automation of methods closer to novices for detection of diseases in due time.

Kaggle Challenge Submission Proof



Results & Scope for the Future

CNNs will greatly improve the computational and processing power in the years to come, thus making things quite easier for the average human.

References:

1. Kaggle.com. 2017. *Intel & MobileODT Cervical Cancer Screening | Kaggle*. [online] Available at: <https://www.kaggle.com/competitions/intel-mobileodt-cervical-cancer-screening/overview> [Accessed 8 April 2022].
2. Lin, T., RoyChowdhury, A. and Maji, S., 2022. *Bilinear CNN Models for Fine-Grained Visual Recognition*. [online] Cv-foundation.org. Available at: <https://www.cv-foundation.org/openaccess/content_iccv_2015/html/Lin_Bilinear_CNN_Models_ICCV_2015_paper.html> [Accessed 8 April 2022].
3. Sharma, P., Berwal, Y. and Ghai, W., 2020. Performance analysis of deep learning CNN models for disease detection in plants using image segmentation. *Information Processing in Agriculture*, 7(4), pp.566-574.