National College of Ireland

Configuration Manual

MSc Research Project
MSc Data Analytics

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MSc Project Submission Sheet

School of Computing

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Programme: MSc Data Analytics **Year:** 2022-2023

Module: Research Project

Lecturer: Mr Aaloka Anant

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Project Title: Skin Lesion Classification Based on Various Machine Learning Models Explained by Explainable Artificial Intelligence

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Configuration Manual

Skin Lesion Classification Based on Various Machine Learning Models Explained by Explainable Artificial Intelligence

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1 Introduction

The aim of this project is to build a classification model based on a machine learning model, the XGB Classifier, and two convolutional neural network models. and with the help of SHAP and LIME, explain the decision-making process. In this document important code snippets are present that can be used to recreate the project code.

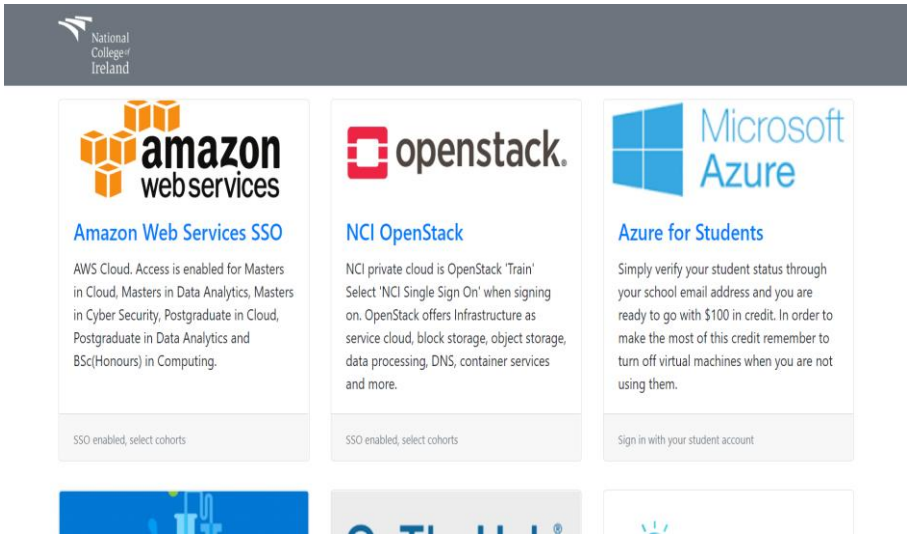
2 System Requirements

To implement this project, the Amazon Web Services platform was used to run the proposed models, which required high computational power.

2.1 Software Configuration

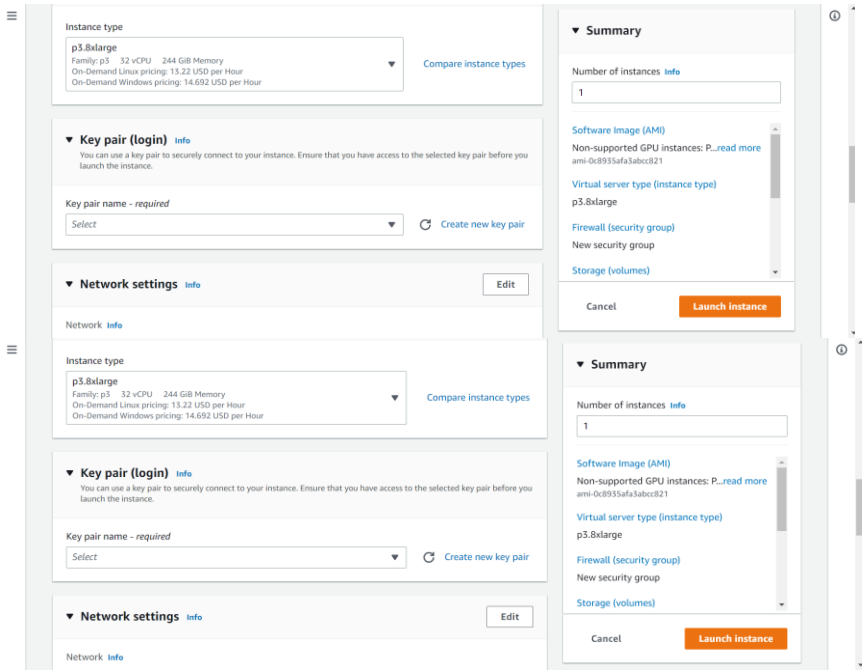
Amazon Web Services Setup

- Go to https://cloud.ncirl.ie/ and click on aazon web services



Create an EC2 Instance

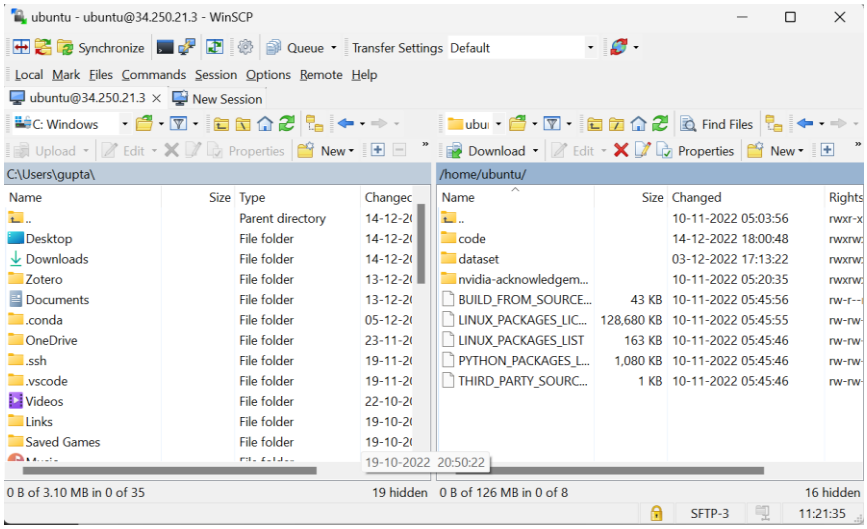
- Using the settin shown in the screenshot, create an instance



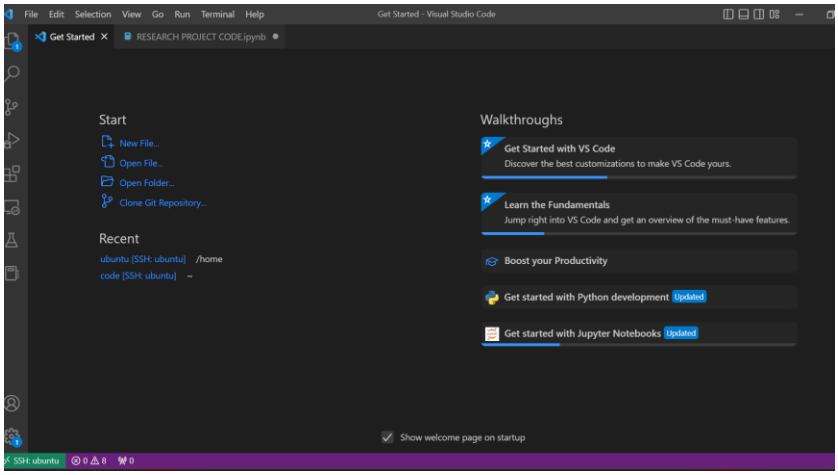
- Select 75 GB as storage of the setup

The following should be the setup of the instance.

- To transfer files WinSCP is used with the credentials



- To run the python script, we used visual studio code connected to the server via credentials



3 Environment Setup

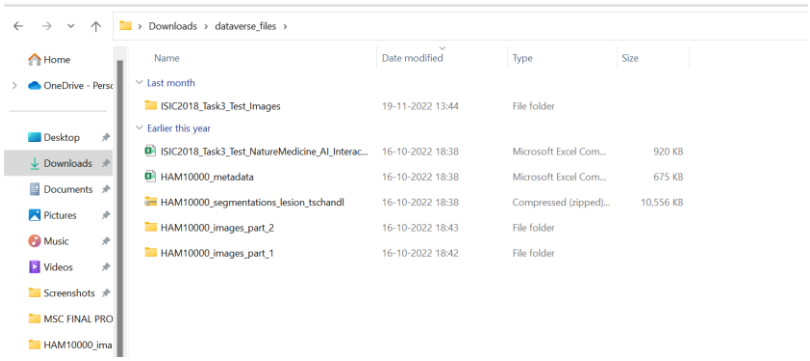
The following libraries are installed and imported.

```
Pandas
Numpy
CV2
Matplotlib
OS
TenserFlow
Keras
LIME
SHAP
Seaborn
Sklearn
xgboost
```

4 Implementation

4.1 Data Collection

- The dataset was downloaded for the Havard Dataverse website and should be unzipped before use. The link of the dataset is provided below https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T



- The CSV file path is given to the and imported in the environment.

```
metadata=pd.read_csv('/home/ubuntu/dataset/HAM10000_metadata.csv', on_bad_lines='skip')
```

```
metadata.sample(n=5)
```

	lesion_id	image_id	dx	dx_type	age	sex	localization	dataset
3845	HAM_0006947	ISIC_0031662	nv	histo	45.0	female	foot	rosendahl
7902	HAM_0002015	ISIC_0033771	nv	histo	30.0	female	lower extremity	vidir_modern
1472	HAM_0002032	ISIC_0030575	mel	histo	25.0	male	back	rosendahl
2723	HAM_0004662	ISIC_0024331	bcc	histo	65.0	male	lower extremity	rosendahl
2810	HAM_0006386	ISIC_0029035	bcc	histo	70.0	male	face	rosendahl

```
metadata.rename(columns = {'localization':'lesion_location'}, inplace = True)
metadata.rename(columns = {'dx':'lesion_type'}, inplace = True)
metadata.rename(columns = {'dx_type':'lesion_confirmation_type '}, inplace = True)
```

4.2 Data Preprocessing

- Null values are removed using the following code

```
metadata['age'].fillna((metadata['age'].mean()), inplace=True)
metadata.isnull().sum()
```

- Data visulasization is done using matplotlib, seaborn

4.3 Data Transformation

- The images from the dataset were resized fro 450*600 to 120*160

```
metadata['image'] = metadata['path'].map(lambda x: np.asarray(Image.open(x).resize((160,120))))
```

- The dataset is splitted into test and train

```
features=metadata.drop(columns=['lesion_type_categorical','dataset'],axis=1)
target=metadata['lesion_type_categorical']


trainX, testX, trainY, testY = train_test_split(features, target, test_size=0.20,random_state=1234)
```

- The dataset is Standardized
- The attributes of the dataset are converted to categorical values.

4.4 Model Building

- Three models are proposed in this dataset two built on the same CNN architecture
- CNN Architecture

```
# CNN Model Architecture
input_shape = (120, 160, 3)
num_classes = 7

model = Sequential()
model.add(Conv2D(16, (3, 3), padding='same',input_shape=input_shape, activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Dense(num_classes, activation='softmax'))

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

Model 1 CNN on orignal dataset

- Model fitting CNN on original dataset.

```
Epochs=50
batchSize=5
t0=time.time()
# model fit

print('-----------------------------------------------')
print('Running Model 1 without data augmentation.')
print('-----------------------------------------------')
ModelT = model.fit(x_train, y_train,
                   validation_data=(x_test, y_test),
                   epochs=Epochs,
                   batch_size=batchSize,
                   verbose=1)

print('-----------------------------------------------')
t1=time.time()
print(t1-t0," seconds")
```

Mdel 2 CNN after Image Augmentation

- Image augmentation

```
trainDatagen = ImageDataGenerator(
    rotation_range = 20, # Tried a variety of rotations but made little difference
    width_shift_range = 0.1,  # 0.2
    height_shift_range = 0.1, # 0.2
    #shear_range = 0.1,  # 0.2
    zoom_range = 0.1, # 0.2, 0.3
    horizontal_flip = True,
    #vertical_flip = True # tended to add a bit more overfitting
)

trainDatagen.fit(x_train) # fit the training data in order to augment.
```

- Model fit after Image augmentation

```
epochs = 50
batchSize = 10
t0=time.time()

print('-----------------------------------------------')
print('Running Model 2 - Data Augumentation Included.')
print('-----------------------------------------------')

Model = model.fit_generator(trainDatagen.flow(x_train,y_train, batch_size=batchSize),
                            epochs = epochs, validation_data = (x_validate,y_validate),
                            verbose = 1, steps_per_epoch=x_train.shape[0] // batchSize,
                            callbacks=[lrReduction])

t1=time.time()
print(t1-t0," seconds")
```

Model 3 XGB Classifier

- Categorization of columns
- Split into test and train

```
X = tile_df[features]
y = tile_df['lesion_type_categorical'].values
X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=0)
```

- Model fit

```
model = XGBClassifier(random_state=1)
model = model.fit(X_train, y_train)
```

5 Evaluation

Results of Model are calculated using the same code as the model are same but different parameters there the following snippets can be used to evaluate all the models.

- For model accuracy and loss

```
print('-----------------------------------')
print('Model 2 Accuracy and Loss Scores')
print('-----------------------------------')
scores = model.evaluate(x_test, y_test, verbose=2)

print("CNN Error: %.2f%%" % (100-scores[1]*100))
print("CNN Acc: %.2f%%" % (scores[1]*100))

final_loss, final_acc = model.evaluate(x_test, y_test, verbose=1)
print("Final loss: {0:.4f}".format(final_loss, final_acc))
print('-----------------------------------------')
```

- To generate classification report

```
from sklearn.metrics import classification_report
print('Model 2 Classification Report')
print('---------------------------------------')

model_report= classification_report(y_true, y_pred, target_names=targetNames)
print(model_report)
```

- To calculate area under the curve

```
def multiclass_roc_auc_score(y_test, y_pred, average="macro"):
    lb = preprocessing.LabelBinarizer()
    lb.fit(y_test)
    y_test1 = lb.transform(y_test)
    y_pred1 = lb.transform(y_pred)
    return roc_auc_score(y_test1, y_pred1, average=average)

aucScore =multiclass_roc_auc_score(y_test, y_pred)
print('-----------------------------------')
print('Model 2 Area Under Curve')
print('-----------------------------------')
print("AUC: %.2f%%" % (aucScore*100))
```

- To calculate confusion matrix

```
confusion_mtx = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(9,6))

sns.heatmap(confusion_mtx, annot=True, fmt='d',cmap=plt.cm.BuPu )
plt.show()
```

6 Explainable AI

- To implement install LIME AND SHAP Using !pip install command.

SHAP explainer

- Define model and SHAP Value

```
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(X_test)
```

- Create plots to explain the models using the following codes

```
shap.summary_plot(shap_values, X_test, plot_type="bar")
```

```
shap.summary_plot(shap_values[0], X_test)
```

```
shap.initjs()
shap.force_plot(explainer.expected_value[0], shap_values[0][:100,:], X_test.iloc[:100,:])
```

```
shap.initjs()
shap.force_plot(explainer.expected_value[0], shap_values[0][15,:], X_test.iloc[15,:])
```

LIME Explainer

Install and import LIME

- LIME is inputted CNN model to explain the images

```
np.random.seed(222)

Xi = x_test[0]
preds = model.predict(Xi[np.newaxis,:,:,:])
top_pred_classes = preds[0].argsort()[-7:][::-1] # Save ids of top 5 classes
top_pred_classes
```

- The following code can be used to proce explaination for an image present in the datset
- Select an image at random from the datset to provide explainations

```
#Generate segmentation for image
superpixels = skimage.segmentation.quickshift(Xi, kernel_size=4,max_dist=200, ratio=0.2)
num_superpixels = np.unique(superpixels).shape[0]
skimage.io.imshow(skimage.segmentation.mark_boundaries(Xi, superpixels))
print("The number of super pixels generated")
num_superpixels
```

```
#Generate perturbations
num_perturb = 150
perturbations = np.random.binomial(1, 0.5, size=(num_perturb, num_superpixels))

#Create function to apply perturbations to images
import copy
def perturb_image(img,perturbation,segments):
    active_pixels = np.where(perturbation == 1)[0]
    mask = np.zeros(segments.shape)
    for active in active_pixels:
        mask[segments == active] = 1
    perturbed_image = copy.deepcopy(img)
    perturbed_image = perturbed_image*mask[:,:,np.newaxis]
    return perturbed_image

#Show example of perturbations
print(perturbations[0])
```

```
skimage.io.imshow(perturb_image(Xi,perturbations[5],superpixels))
```

```
#Estimate linear model
from sklearn.linear_model import LinearRegression
class_to_explain = 4
simpler_model = LinearRegression()
simpler_model.fit(X=perturbations, y=predictions[:,:,class_to_explain], sample_weight=weights)
coeff = simpler_model.coef_[0]

#Use coefficients from linear model to extract top features
num_top_features = 4
top_features = np.argsort(coeff)[-num_top_features:]

#Show only the superpixels corresponding to the top features
mask = np.zeros(num_superpixels)
mask[top_features]= True #Activate top superpixels
skimage.io.imshow(perturb_image(Xi,mask,superpixels))
```