

Configuration Manual

MSc Research Project Data Analytics

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Configuration Manual

Arpita Mitra x21116211

1 Introduction

The scripts employed in this study have certain instructions that must be followed, which are outlined in the configuration manual. You will find that following the instructions in this tutorial will help you successfully execute the code. In addition to that, this documentation includes information on the hardware design of the machine on which the code was implemented. In addition to this, the system's most basic configuration requirements are also listed.

2 System Specification

The below table 1 and 2 are listed with all the hardware and software specifications for the platform upon which the research work is being carried out.

2.1 Hardware Specification

Hardware used Specification	
Processor	Intel(R) Core(TM) i7 8th generation
RAM	16 GB
Hard Drive	1 TB

 Table 1: Hardware Specification

2.2 Software Specification

Software used	Version
Operating System	Windows-10 Home, 64 bit Operating
	System
Anaconda Navigator	2022.05
Python	3.9.12
Power Bi	2.100.1401.0

 Table 2: Software Specification

3 Environment Set Up

The entire research was done by writing Python code in Jupyter Notebook on Anaconda Navigator. First, Anaconda Navigator needs to be installed.

OANACONDA. Products - Pricing Solutions - Resource	ces 👻 Partners 👻 Blog Company 👻 Contact Sales
	Anaconda Distribution
The world's most popular open- source Python distribution platforn	Download # For Windows Python 3.9 • 64-Bit Graphical Installer • 621 MB
	Get Additional Installers

Figure 1: Anaconda Navigator Installation

The Anaconda Navigator can be accessed through Start, then select Anaconda Navigator after the installation has been completed successfully. Then Jupyter notebook can be launched from Anaconda Navigator.

	DA.NAVIGATOR						Connect
A Home	All applications v on	base (root)					
Environments	0	*	*	۰ 🚬	•	•	
🗳 Learning	DataSpell	CMD.exe Prompt	JupyterLab	Notebook	Powershell Prompt	Qt Console	
Community	DataSpell is an IDE for exploratory data analysis and prototyping machine learning models. It combines the interactivity of Jugster notebooks with the intelligent Python and R coding assistance of PyCharm	0.1.1 Run a cmd.exe terminal with your current environment from Navigator activated	An extensible orrivonment for interactive and reproducible computing, based on the Jupyter Notebook and Architecture.	A 6.63 Web-based, interactive computing notebook environment. Edit and run human-readable docs while describing the data analysis.	0.0.1 Run a Powershell terminal with your current environment from Navigator activated	PyQt GUI that bis populs inline figures, proper multiple adding with syntax highlighting, graphical calities, and more.	
	in one user-friendly environment.	Launch	Launth	Launth	Launth	Launth	
	*	•	`	*	Cloud Infrastructure		
	Spyder 3.5.5 Scientific Y thon Development Envilonment, Power (Lip ython IDE with advanced editing, interactive testing,	Datalore Nick-start your data science projects in seconds in a pre-configured environment. Enjoy coding assistance for Python, SQL,	Deepnote Deepnote is a notebook built for collaboration. Create notebooks in your browser, spin up your conde environment	IBM Watson Studio Cloud IBM Watson Studio Cloud provides you the tools to analyze and visualize data, to cleanse and shape data, to create and train	Oracle Data Science Service OCI Data Science offers a machine learning platform to build, train, manage, and deplog your machine learning models on the cloud wich your favorise gene-source	Cluevic 1.0.0 Multidimensional dota visualization across files. Explore relationships within and among related datasets.	
Inaconda lotebooks loud notebooks with undreds of packages eady to code.	debugging and introspection features	and R in Jupyter notebooks and benefit from no-code automations. Use Datalore online for free.	in seconds and share with a link.	machine learning models. Prepare data and build models, using poen source data science tools or visual modeling.	the cloud with your ravoite open-source tools	Install	
Learn More	* 000	¢ PC	R				
Documentation	Orange 3	PyCharm Professional	RStudio				
Aneconde Blog	3.32.0 Component based data mining framework. Data visualization and data analysis for novice and expert. Interactive workflows	A full-fledged IDE by JetBrains for both Scientific and Web Python development. Supports HTML, JS, and SQL	1.1.455 A set of integrated bools designed to help you be more productive with R. Includes R essentials and notebooks.				

Figure 2: Jupyter Access

4 Data Source

Dataset has been collected from Kaggle. This research project has been carried out using the dataset ¹ created by Ali et al. (2022) which was made publicly available by the authors for future research.

¹https://www.kaggle.com/datasets/nafin59/monkeypox-skin-lesion-dataset?datasetId= 2308447

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	Create	NAVISAGETS AND 3 COLLABORATORS - UPDATED 5 MONTHS ADD New Notebook New Notebook	초 Download (49 MB) @	
	Home			
	Competitions	Monkeypox Skin Lesion Dataset	0 0 2	
	Datasets	Binary classification data for Monkeypox vs Non-monkeypox (Chickenpox, Measles)		1907
				1000
	Code			A
	Code Discussions	· · · · · ·		6
		Data Card Code (23) Discussion (0)		8
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	Discussions Learn	Data Card Code (23) Discussion (0) About Dataset	Usability © 7.65	
	Discussions Learn More		7.65	
	Discussions Learn More Your Work	About Dataset Context The recent nonkeypor outbreak has become a global healthcare concern owing to its rapid spread in more than 65 countries around the	7.65 License Attribution-NonCommerce	cial 4.0
	Discussions Learn More Your Work RECENTLY VIEWED	About Dataset Context	7.65 License Attribution-NonCommerce	

Figure 3: Monkeypox Dataset

The dataset has been downloaded in a zip format. Further, it was unzipped in the local drive and then the entire research was performed using the same dataset.

5 Implementation

The design of this study, as well as its execution, makes use of the following libraries mentioned in table 3 that has to be installed to conduct this research study.

Libraries used	Version
Numpy	1.21.5
Pandas	1.4.2
Scikit-learn	1.0.2
Keras	2.11.0
TensorFlow	2.11.0
Matplotlib	3.5.1

Table 3: Libraries used in this study

The study procedure, along with its methodology, will be broken down into its component parts in the following sections.

5.1 Blocks of Code:

Import Libraries

The below screenshot depicts all the necessary libraries that are used in this study.

# Import relevant libraries and packages	
import glob	
import os	
from PIL import Image	
from PIL import ImageFilter	
import pandas as pd	
import numpy as np	
import shutil	
<pre>import matplotlib.pyplot as plt</pre>	
import matplotlib.image as mpimg	
import scikitplot as skplt	
<pre>import matplotlib.pyplot as plt</pre>	
from tensorflow import keras	
from keras.preprocessing.image import ImageDataGenerator	
from keras.models import Sequential, load_model	
from keras.callbacks import EarlyStopping	
from keras.layers import Conv2D, MaxPooling2D	
from keras.layers import Activation, Dropout, Flatten, Dense	
from keras import optimizers	
from keras.applications.vgg19 import VGG19	
<pre>from sklearn.metrics import confusion_matrix, precision_score, recall_score</pre>	
import matplotlib.pyplot as plt	
np.random.seed(123)	
import itertools	
from sklearn metrics import fl score	

Figure 4: Import Libraries

Data Pre-processing

The below block of code creates the train, validation and test folders inside the root directory of each class of images and then data was shuffled randomly and split into 70:15:15 ratio, and then it was stored in its respective directories.

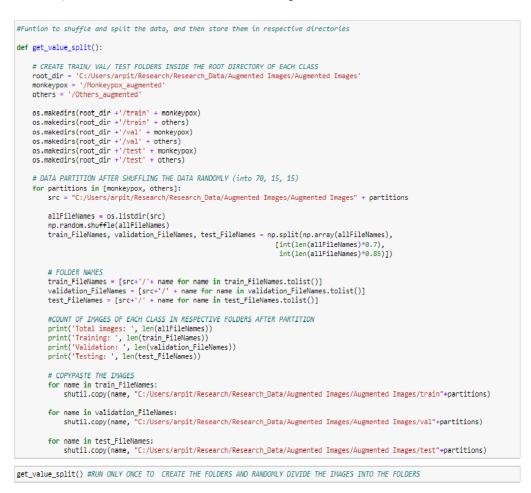


Figure 5: Shuffle & split the data

To create more complexity in the model, more blurry images were added to the existing data.

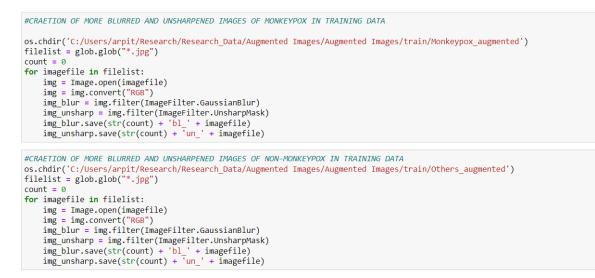


Figure 6: Adding blurry images to dataset

CNN Model

CNN Model building

```
#GET THE MODEL TO OUTPUT 3D FEATURE MAPS (HEIGHT, WIDTH, FEATURES)
model = Sequential()
# Layer 1
model.add(Conv2D(32, (3, 3), input_shape=(228, 228, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
# Laver 2
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
# Layer 3
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
# APPLY THE FLATTENING FUNCTION TO CONVERT 3D FEATURE MAPS INTO 1D FEATURE VECTORS
model.add(Flatten())
# ADD 2 FINAL DENSE LAYERS TO ADD A CLASSIFIER TO THE CONVOLUTIONAL BASE
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))
# COMPILE THE MODEL
model.compile(loss='binary_crossentropy',
                  optimizer='rmsprop',
metrics=['accuracy'])
# PRINTING THE MODEL SUMMARY
print(model.summary())
```

Figure 7: CNN Model

Data Augmentation & Training of CNN Model

Data Augmentation & Training of the model

```
# DEFINE BATCH SIZE & TARGET SIZE
batch_size = 50 # batch size defines how many images will be sent over the network at a time
target_size = (228, 228) #image size
 # CONFIGURE AUGMENTATION FOR TRAINING ADVERSITY
 # ImageDataGenerator rescales the pixels between zero and one
 train_datagen = ImageDataGenerator(
    rescale=1./255,
         shear_range=0.2,
zoom_range=0.2,
         horizontal flip=True)
 # SET AUGMENTATION FOR TESTING
 test_datagen = ImageDataGenerator(rescale=1./255)
 # READ PICTURES IN TRAINING DIRECTORY AND GENERATE BATCHES OF IMAGE DATA
batch_size=batch_size,
class_mode='binary')
 # SAME GENERATOR AS ABOVE, BUT FOR VALIDATION DATA
target size=target size.
         batch_size=batch_size,
class_mode='binary')
Found 6699 images belonging to 2 classes.
Found 479 images belonging to 2 classes.
  SET STOP TO 5 EPOCHS TO PREVENT OVERFITTING OF THE MODEL
callback = EarlyStopping(
    monitor='val_acc',
    restore_best_weights=True,
patience=5
)
# SAVE WEIGHTS AFTER IMPLEMETING CALLBACK TO LATER COMPARE MODEL
history = model.fit(
    train_generator,
          steps_per_epoch=6699 // batch_size, #6699 IS THE TRAIN_GENERATOR RESULT
epochs=30, # NUMBER OF EPOCH MEANS THE RUNNING SPEED OF THE MODEL
```

```
epochs=30, # NUMBER OF EPOCH MEANS THE RUNNING SPEED OF THE MODEL
validation_data=validation_generator,
validation_steps=479 // batch_size, #479 IS VALIDATION_GENERATOR RESULT
callbacks=[callback]
)
# CREATE DIRECTORY TO SAVE RESULTS OF THE MODEL
os.mkdir('C:/Users/arpit/Model_Results')
model.save('Model_Results')
```

Figure 8: Training of CNN model

Training of the CNN model will take $\tilde{}$ 3 hours to complete.

Validation of CNN Model

Validation of CNN Model

Figure 9: Validation of CNN model

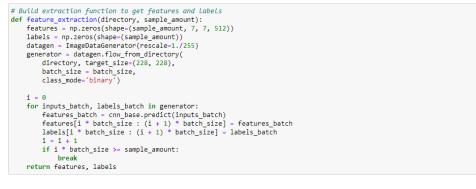
VGG 19 Model

VGG 19 Model
<pre># Build VGG19 structure cnn_base = VGG19(weights='imagenet',</pre>

Figure 10: Structure of VGG 19 Model

The bottlenecked characteristics of the model was retained after the extraction process, and a classifier comprising final dense layers has been appended to the model. Using the below blocks of code, features and labels had been extracted and applied to train, validation and test set and the same was saved in a form of Numpy array for later use.

Feature Extraction



Train the model

Apply extraction function to 3 datasets
train_features, train_labels = feature_extraction(training_folder, train_samples)
validation_features, validation_labels = feature_extraction(validation_folder, validation_samples)
test_features, test_labels = feature_extraction(testing_folder, test_samples)

Figure 11: Feature Extraction

# Save the extracted features and labels in a	directory	
os.mkdir('C:/Users/arpit/Research/Research_Da	ta/Augmented Images/Augmented	d Images/bottlenecked')
np.save('C:/Users/arpit/Research/Research_Dat	a/Augmented Images/Augmented	Images/bottlenecked/train_features.npy', train_features
np.save('C:/Users/arpit/Research/Research_Dat	a/Augmented Images/Augmented	<pre>Images/bottlenecked/train_labels.npy', train_labels)</pre>
np.save('C:/Users/arpit/Research/Research_Dat	a/Augmented Images/Augmented	Images/bottlenecked/validation_features.npy', validation
np.save('C:/Users/arpit/Research/Research_Dat	a/Augmented Images/Augmented	Images/bottlenecked/validation_labels.npy', validation
np.save('C:/Users/arpit/Research/Research_Dat	a/Augmented Images/Augmented	<pre>Images/bottlenecked/test_features.npy', test_features)</pre>
<pre>np.save('C:/Users/arpit/Research/Research_Dat</pre>	a/Augmented Images/Augmented	<pre>Images/bottlenecked/test_labels.npy', test_labels)</pre>

Figure 12: Saving Extracted Features

VGG 19 Models Validation

VGG-19 Model 1

Validation

VGG-19 Model 1 (with 2 dense layers)

<pre># Build classifier on top of VGG19 model = Sequential()</pre>
Add dense layers on top of VGG19 # 1
<pre>model.add(Dense(256, activation='relu', input_dim=reshape_y)) # 2</pre>
<pre>model.add(Dense(1, activation='sigmoid'))</pre>
<pre># Compile the model model.compile(optimizer=optimizers.RMSprop(lr=1e-4),</pre>
<pre>history = model.fit(train_features, train_labels,</pre>
<pre># Save VGG19 results model.save('Model_Results/model_VGG_01.h5')</pre>

Figure 13: VGG 19 Model 1

Previously extracted saved features were reloaded to use in other models as they have dropout layers appended to them.

VGG-19 Model 2

VGG-19 Model 2 (3 dense layers + 1 Dropout layer)	
count = 2	
<pre>count = 2 # Deeper VGG19 network model = Sequential() # 1 model.add(Dense(256, activation='relu', input_dim=train_features.shape[1])) # 2 model.add(Dropout(0.2)) # 3 model.add(Dense(64, activation='relu')) # 4 model.add(Dense(64, activation='relu')) # 4 model.compile(optimizer=optimizers.RMSprop(lr=1e-4),</pre>	
<pre>count += 1 plt.show()</pre>	

Figure 14: VGG 19 Model 2

VGG-19 Model 3

VGG-19 Model 3 (Reduced learning rate 1e-2)

```
# Reduce learning rate to 1e-2
model = Sequential()
# 1
model.add(Dense(256, activation='relu', input_dim=train_features.shape[1]))
# 2
model.add(Dropout(0.2))
# 3
model.add(Dense(64, activation='relu'))
# 4
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer=optimizers.RMSprop(lr=1e-2),
                  loss='binary_crossentropy',
metrics=['acc'])
history = model.fit(train_features, train_labels,
                         epochs=30,
                         batch_size=50,
validation_data=(validation_features, validation_labels))
model.save(f'Model_Results/model_VGG_0{count}.h5')
pd.DataFrame(history.history).plot(figsize=(5, 5))
plt.title(f'Pre-Trained Training Performance: Model {count}')
plt.xlabel('Epoch')
plt.ylabel('Metric')
count += 1
plt.show()
```

Figure 15: VGG 19 Model 3

VGG-19 Model 4

```
VGG-19 Model 4 (with Adam Optimizer)
```

```
# Try adam optimizer
model = Sequential()
# 1
model.add(Dense(256, activation='relu', input_dim=train_features.shape[1]))
# 2
model.add(Dropout(0.2))
# 3
model.add(Dense(64, activation='relu'))
# 4
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(train_features, train_labels,
                    epochs=30,
                    batch size=50,
                    validation_data=(validation_features, validation_labels))
model.save(f'Model_Results/model_VGG_0{count}.h5')
pd.DataFrame(history.history).plot(figsize=(5, 5))
plt.title(f'Pre-Trained Training Performance: Model {count}')
plt.xlabel('Epoch')
plt.ylabel('Metric')
count += 1
plt.show()
```

Figure 16: VGG 19 Model 4

VGG-19 Model 5 (with 2 dense layers + 1 Dropout layer)

```
# Shallower network
model = Sequential()
# 1
model.add(Dense(256, activation='relu', input_dim=train_features.shape[1]))
# 2
model.add(Dropout(0.2))
# 3
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer=optimizers.RMSprop(lr=5e-6),
              loss='binary_crossentropy',
metrics=['acc'])
history = model.fit(train_features, train_labels,
                     epochs=30,
                     batch_size=50,
                     validation_data=(validation_features, validation_labels))
model.save(f'Model_Results/model_VGG_0{count}.h5')
pd.DataFrame(history.history).plot(figsize=(5, 5))
plt.title(f'Pre-Trained Training Performance: Model {count}')
plt.xlabel('Epoch')
plt.ylabel('Metric')
count += 1
plt.show()
```

Figure 17: VGG 19 Model 5

Testing the Models

<pre># Print scores of baseline CNN model usine ImagedataGenerator model_baseline.evaluate(test_generator,</pre>
9/9 [======] - 6s 703ms/step - loss: 0.2413 - accuracy: 0.9000
[0.24128085374832153, 0.8999999761581421]
<pre># Get pretrained test features containing the weights test_features = np.load('C:/Users/arpit/Research/Research_Data/Augmented Images/Augmented Images/bottlenecked/test_features.npy') test_labels = np.load('C:/Users/arpit/Research/Research_Data/Augmented Images/Augmented Images/bottlenecked/test_labels.npy')</pre>
۲. () () () () () () () () () (
<pre># Print model scores for model_name, model in models_VGG.items(): print(model_name + ' Evaluation') print(model.evaluate(test_features, test_labels)) print()</pre>
model_VGG_01.h5 Evaluation 15/15 [====================================
model_VGG_02.h5 Evaluation 15/15 [====================================
model_VGG_03.h5 Evaluation 15/15 [====================================
model_VGG_04.h5 Evaluation 15/15 [====================================
model_VGG_05.h5 Evaluation 15/15 [====================================

Figure 18: Model Testing

References

Ali, S. N., Ahmed, M. T., Paul, J., Jahan, T., Sani, S. M. S., Noor, N. and Hasan, T. (2022). Monkeypox skin lesion detection using deep learning models: A preliminary feasibility study, arXiv preprint arXiv:2207.03342.