

# Configuration Manual

MSc Research Project Data Analytics

Sanjeet Shekhar Student ID: 23209470

School of Computing National College of Ireland

Supervisor: Shubham Subhnil

#### **National College of Ireland**



### **MSc Project Submission Sheet**

### **School of Computing**

	Sanjeet Shekhar	
Student Name:		
	23209470	
Student ID:	MSc. Data Analytics 20	
Programme:		
	MSc. Research Project	
Module:	Shubham Subhnil	
Lecturer: Submission Due Date:	12/12/2024	
	Diabetic retinopathy detection a comparison of several CNN models	
Project litie:	and optimizers	_
	371 5	
<b>Word Count:</b>	Page Count:	
required to use	aterial must be referenced in the bibliography section the Referencing Standard specified in the report temple or electronic work is illegal (plagiarism) and may re-	late. To use other
Signature:		
Signature.		
Date:		
_		
Date:		
Date: PLEASE READ		Γ
Date: PLEASE READ  Attach a comple copies) Attach a Mood	THE FOLLOWING INSTRUCTIONS AND CHECKLIST	Γ
PLEASE READ  Attach a comple copies)  Attach a Mood submission, to You must ensured for your own ref	THE FOLLOWING INSTRUCTIONS AND CHECKLIST ted copy of this sheet to each project (including multip	r ole   -

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

# **Configuration Manual**

Sanjeet Shekhar Student ID: 23209470

#### 1 Introduction

The research is about comparing CNN models to get better understanding of which model is best for performing image classification. The work compares ResNet vs MobileNet vs EffcientNet to classify the dataset containing 5 stages of Diabetic Retinopathy. The work also compares the efficiency and accuracy of the model based on the optimizer chosen. ADAM optimizer is compared to Stochastic Gradient Descent (SGD) optimizer in order to find out the best optimizer for the use case.

Following is the step-by-step process demonstrating the project setup and system requirements along with the tools and libraries that are required to run the code.

### 2 System Configuration

The analysis work is done on Google-based cloud platform Google Colaboratory (colab). The Pro version of Google colab comes with GPU and RAM options.

The following screenshots show the System configuration for colab used in the project.

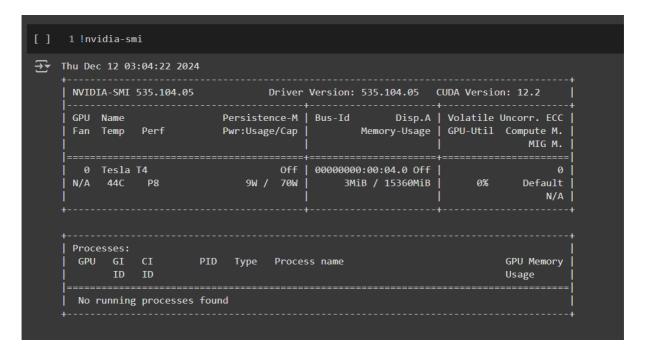


Fig 1 Colab System Specification

#### 3 Data Collection

The dataset used in the research work is collected from open source platform.

Dataset URL: <a href="https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-224x224-gaussian-filtered">https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-224x224-gaussian-filtered</a>

This zip file is then uploaded to the google drive which is accessible by google colab.

```
Imports and Environment Setup
      1 from google.colab import drive # Data loading from google drive
      2 drive.mount('/content/gdrive')
      3 !unzip -q /content/gdrive/MyDrive/dataset/retina_dataset.zip

→ Mounted at /content/gdrive

      1 import os
[ ]
     2 from torchvision.datasets import ImageFolder
     3 data_dir = './gaussian_filtered_images/gaussian_filtered_images'
     4 os.listdir(data dir)
     5 if os.path.exists('./gaussian_filtered_images/gaussian_filtered_images/export.pkl'):
     6 os.remove(data_dir + '/export.pkl') # removing unecessary file from dataset
      7 print(os.listdir(data_dir))
     8 print(ImageFolder(data dir).root)

→ ['Moderate', 'No_DR', 'Mild', 'Severe', 'Proliferate_DR']

     ./gaussian_filtered_images/gaussian_filtered_images
```

Fig 2. Google Drive to colab setup and other environment setup

### 4 Implementation

#### 4.1 Libraries used to research

```
1 # Essential imports
2 import torch
3 import torch.nn as nn
4 import torch.optim as optim
5 from torchvision import datasets, transforms, models
6 from torch.utils.data import DataLoader
7 import time
8 import cv2
9 from torchvision.transforms import ToPILImage, ToTensor, Compose, RandomRotation, Lambda
10 from torch.optim.lr_scheduler import StepLR
11 from torchvision import datasets, transforms
12 from torch.utils.data import DataLoader
```

Fig 3. Libraries used for analysis

The figure shows the libraries used for analysis. Some of the major libraries include

- Torch
- Torchvision
- Cv2

```
14 # Dataset preparation
15 import os
16 import random
17 import shutil
18 from torchvision import datasets, transforms
19 from torch.utils.data import DataLoader, random_split
20
```

Fig 4. Libraries used to set colab and perform other preprocessing steps

```
21 # Visualization setup
22 from torchvision.utils import make_grid
23 import matplotlib.pyplot as plt
24 import numpy as np
25 from scipy.interpolate import make_interp_spline
26
```

Fig 5. Libraries used to perform visualization before and after analysis

#### 4.2 Dataset

The dataset zip file contains 5 directories that contain images of eyes affected by various stages of diabetic retinopathy.

- Mild
- Moderate
- No DR
- Proliferate\_DR
- Severe
- export.pkl (pkl file that needs to be dropped before proceeding)

```
[2] 1 import os
2 from torchvision.datasets import ImageFolder
3 data_dir = './gaussian_filtered_images/gaussian_filtered_images'
4 os.listdir(data_dir)
5 if os.path.exists('./gaussian_filtered_images/gaussian_filtered_images/export.pkl'):
6 os.remove(data_dir + '/export.pkl') # removing unecessary file from dataset
7 print(os.listdir(data_dir))
8 print(ImageFolder(data_dir).root)

The Moderate', 'No_DR', 'Mild', 'Severe', 'Proliferate_DR']
./gaussian_filtered_images/gaussian_filtered_images
```

Fig 6. Directories setup and cleanup of unnecessary files

#### 4.3 The Flow of the Implementation

- Setup directories for image classification
- Visualize the sample images
- Define model architectures
- Setup training and evaluations
- Run and compare models
- Choose best model

• Run training again on same model to compare optimizers



Fig 7. Samples for the loaded and cleaned dataset

```
pit.text(epochs[-1], train_accuracy[-1], c'(train_accuracy[-1], c'(train_accuracy[-1], c'(train_accuracy[-1], c'(train_accuracy[-1], c'(train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], c'(train_accuracy[-1], c'(train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], c'(train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], c'(train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center')

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center']

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center']

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center']

pit.text(epochs[-1], train_accuracy[-1], color='cacle*, here'center']

pit.text(exister)

pit.text(exis
```

Fig 8. Running models to pick the best model.

# 5 Evaluating model performance

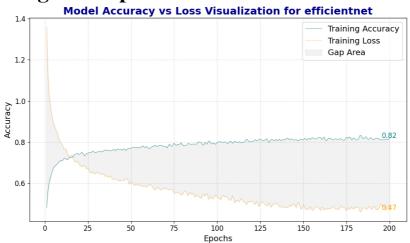


Fig 9. EfficientNet Performance

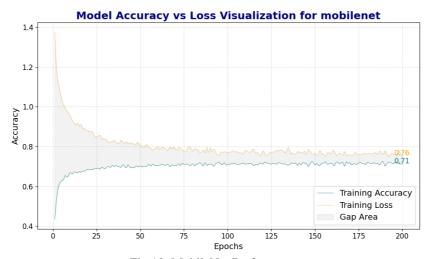


Fig 10. MobileNet Performance

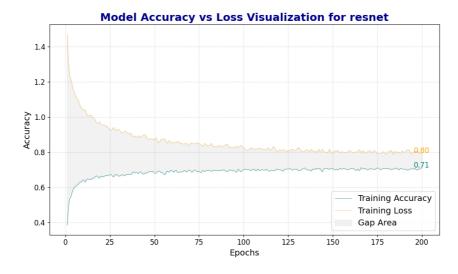


Fig 11. ResNet Performance