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Project Title

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Master of Science in Artificial Intelligence**

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Abstract

Summary of the dissertation **within one page**.

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It is suggested that the abstract be structured as follows:

- Problem: What you tackled, and why this needed a solution
- Objectives: What you set out to achieve, and how this addressed the problem
- Methodology: How you went about solving the problem
- Achievements: What you managed to achieve, and how far it meets your objectives.

Attestation

I understand the nature of plagiarism, and I am aware of the University's policy on this.

I certify that this dissertation reports original work by me during my University project except for the following (*adjust according to the circumstances*):

- The technology review in Section 2.5 was largely taken from [17].
- The code discussed in Section 3.1 was created by Acme Corporation (www.acme-corp.com/JavaExpert) and was used in accordance with the licence supplied.
- The code discussed in Section 3.5 was written by my supervisor.
- The code discussed in Section 4.2 was developed by me during a vacation placement with the collaborating company. In addition, this used ideas I had already developed in my own time.

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Acknowledgements

Acknowledge anyone that you wish to thank who has helped you in your work or supported you in any way: such as your supervisor, technical support staff, fellow students, external organisations or family. Acknowledge the source of any work that is not your own.

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In your document, remove this entire section and only leave the lines

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\tableofcontents  
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1 Introduction

According to the 2019 *WHO* report on vision [1], at least 2.2 billion people across the world are impacted by some vision impairment to a degree. Not only this, but many of these cases go undetected and therefore undergo no treatment or are addressed in an advanced stage of the disease.

As pointed out by the *WHO* in their report [1], certain subsets of the population are more likely to not receive appropriate care, due to factors like income, age or geographical location. The situation is also estimated to get worse over the next decade, due to the combination of population increase and the rise in insurgence of the diseases most commonly associated with vision loss.

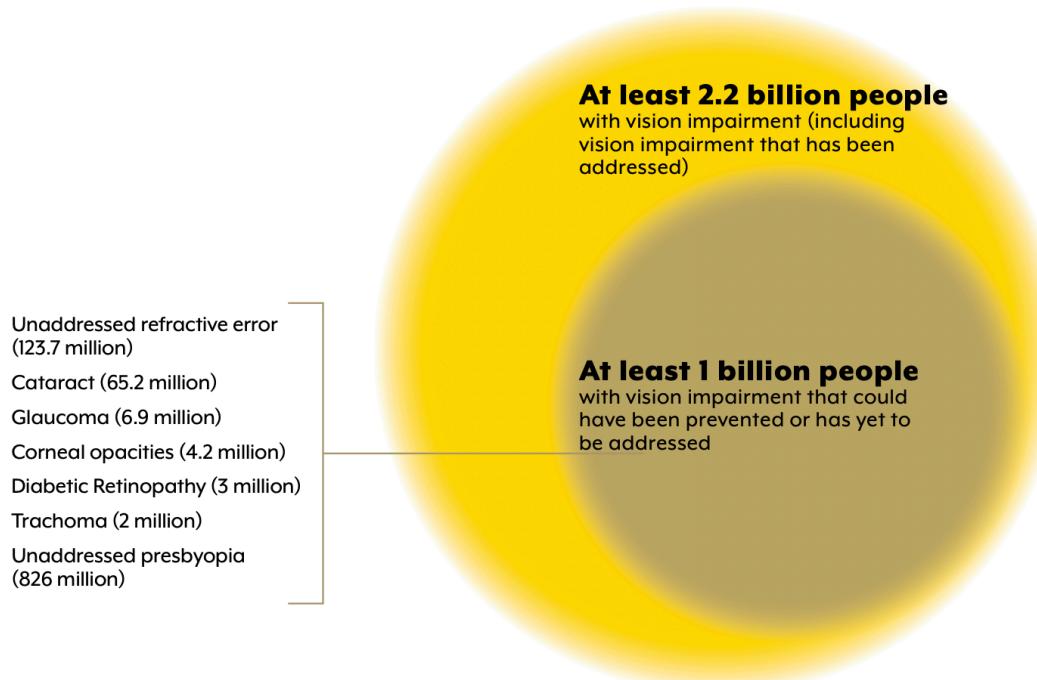


Figure 1.1: Proportion of cases of vision impairment that could have been prevented or addressed [1]

One of the main diagnosis associated with vision impairment and blindness is Diabetic Retinopathy (DR). This condition, which is a consequence of the insurgence of Diabetes Mellitus (DM), is destined to increase in incidence due to the rise in number of diabetic patients, reaching 191 million by 2030 [3].

1.1 Background and Context

1.1.1 Diabetic Retinopathy

Diabetic Retinopathy (DR) is an eye condition which results from Diabetes Mellitus (DM) and it is among those responsible for severe vision loss. As such, the majority of work within Retinal Imaging Analysis is focused on the detection of Diabetic Retinopathy from eye fundus images.

Diabetic Retinopathy is classified as a *microvascular disease* [2], as it entails the rupture of blood vessels within the eye. Its diagnosis originates from the detection of *microvascular lesions* such as:

- Microaneurysms
- Haemorrhages
- Exudates
- Hard exudates

Figure 1.2 shows an example of these lesions:

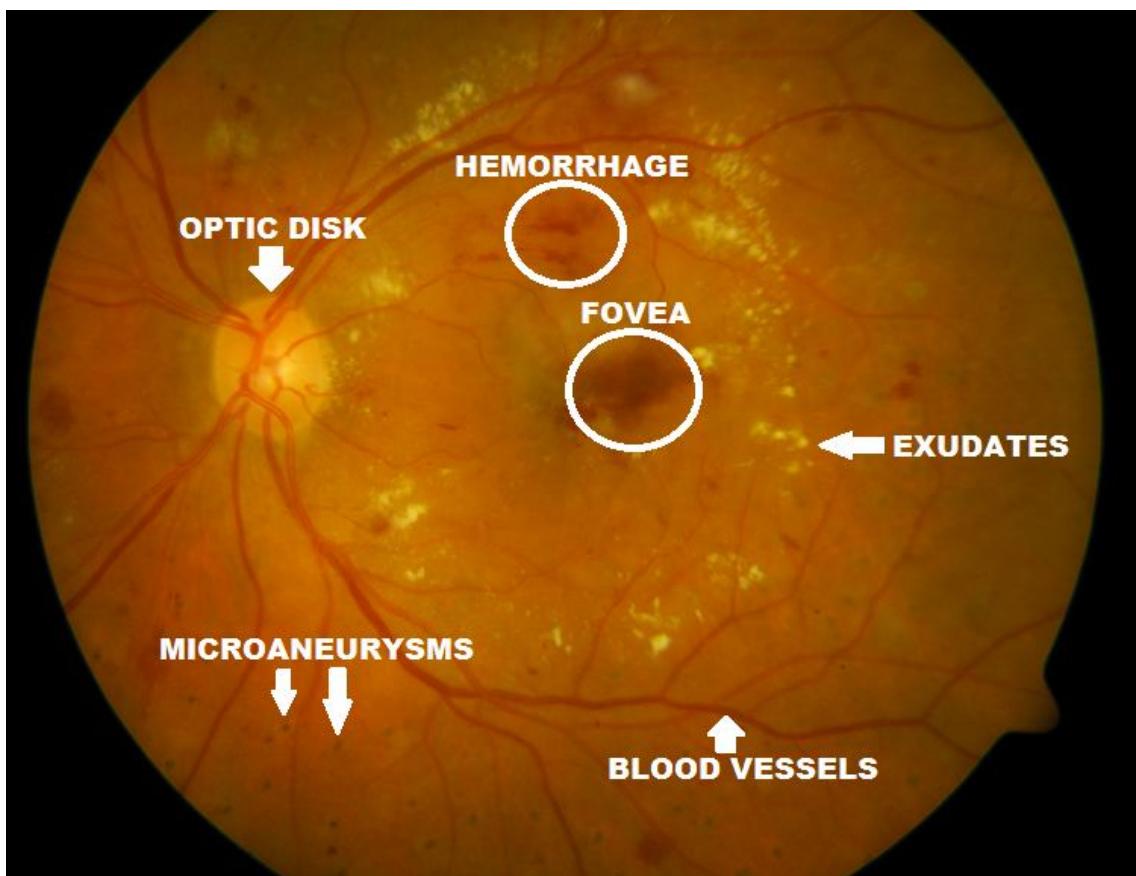
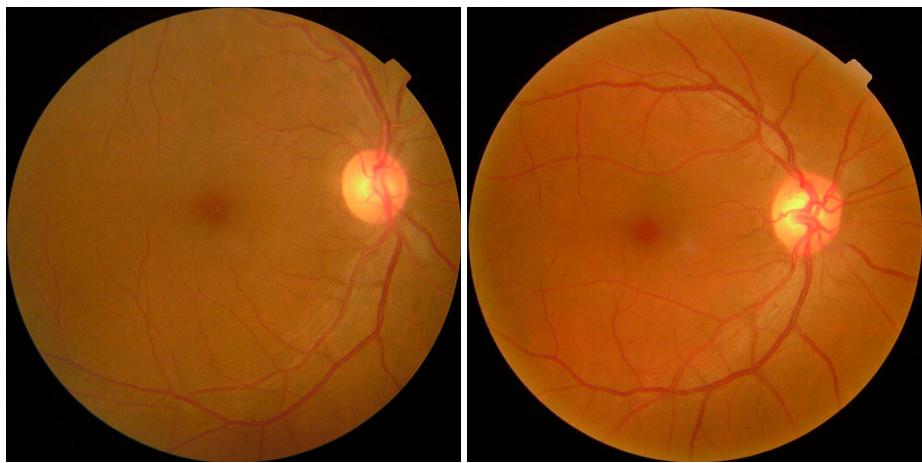


Figure 1.2: Different microvascular lesions associated with Diabetic Retinopathy. Source: [4]

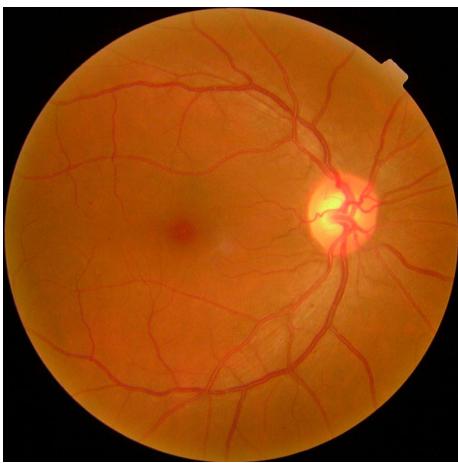
Clinical grading for Diabetic Retinopathy can be provided according to different standards, of which the one proposed by the ETDRS [5] is the most popular. The grading scale used alongside the majority of public datasets resembles that of the ETDRS, although it does not distinguish between Non-High Risk Proliferative DR and High-Risk Proliferative DR. For future reference, the grading used in this project recognizes Diabetic Retinopathy at four different stages:

- Mild non-proliferative DR
- Moderate non-proliferative DR
- Severe non-proliferative DR
- Proliferative DR

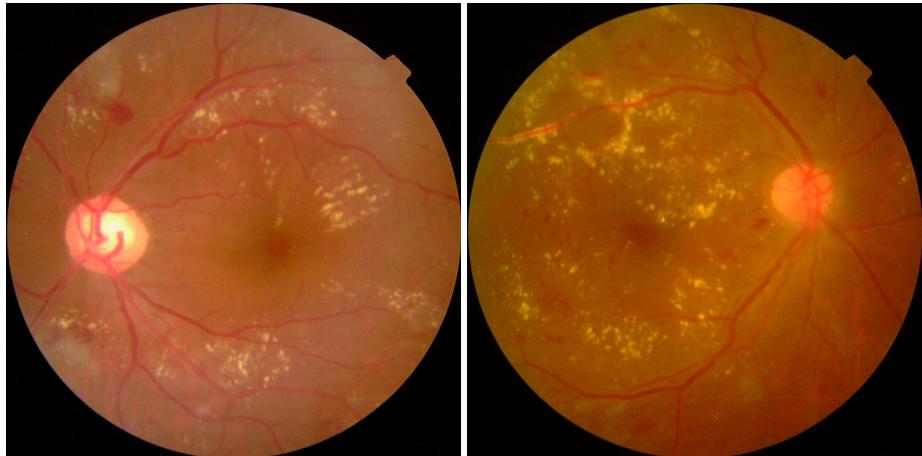
Figure 1.3 shows examples of each stage of Diabetic Retinopathy, with training images taken from the APTOS 2019 Dataset [6].



(a) No DR



(b) Mild DR



(c) Moderate DR

(d) Severe DR



(e) Proliferative DR

Figure 1.3: Stages of Diabetic Retinopathy. Source: APTOS 2019 Dataset [6]

1.1.2 Explainability

A well-known issue related to the employment of Machine Learning Classification methods is the fact that models are usually regarded as "black-box". This is because although they often achieve remarkable results, it is not always clear which features contribute more or less to the final classification. If this is less of an issue in the majority of domains, in the context of a medical diagnosis being able to corroborate the output of the model is a prerogative.

In order for a Machine Learning model to be employed in a clinical setting, it is necessary for the medical equip to reach a high confidence level in its performance. Explainable AI comprises a set of tools that can help move in this direction.

That of **Explainable AI (XAI)** is a newborn field within Artificial Intelligence and it aims to address and solve the issue of result interpretability.

Usually, the more complex the model, the least explainable it is. At the same time, in most cases the more complex the model, the most accurate it is [10]. There is definitely a balance to strike between these two factors, especially in high-risk fields such as that of medical diagnosis.

1.2 Scope and Objectives

The aim of this project is to provide an evaluation of explainable

1.3 Achievements

Summarise what you have achieved.

1.4 Overview of Dissertation

Briefly overview the contents of what follows in the dissertation.

2 State-of-the-Art

This section presents a review of the current State-of-the-Art methods for Diabetic Retinopathy detection and grading, and it gives an overview of recent developments in Explainable AI applied to the medical field. The final section of this chapter will touch upon the different datasets available to the public.

2.1 Diabetic Retinopathy Detection

Several Deep Learning based approaches have been proposed in recent years for the detection and grading of Diabetic Retinopathy. A large part of the available literature focuses on the employment of Convolutional Neural Networks (CNNs) for classification of eye fundus images, which have been proven to yield optimal results. However, more complex and innovative solutions have been developed, together with methods to address low variability in the data, overfitting, image enhancement, and gradability.

2.1.1 Convolutional Neural Networks (CNNs)

A simple classification model is proposed by [17], and it aims to employ the Inception-v3 architecture for classification of preprocessed macula-centered retinal fundus images. In this case, the approach taken is that of transfer learning, in which the network is pre-instantiated with weights originating from training on a different dataset, ImageNet in this case. The final algorithm consisted of an ensemble of 10 networks trained on the same data and it was able to provide grading on 4 different levels of disease, including an indication of referable diabetic macular edema (ME). The model was trained on the EyePACS dataset and validated on both EyePACS and Messidor-2, achieving an average sensitivity of 88.3%, and an average specificity of 98.6%.

The CNN method proposed by Tymchenko et. al [15] was replicated, as implemented by [16]. The test accuracy score achieved was 0.872, which is considerably lower than the accuracy advertised by the authors, which is 0.928. However, the code implementation used for the replication advertises a Test Accuracy of 0.576.

The model was trained on the APTOS 2019 Dataset [6], although the test set was derived from the set of training images due to the lack of labels of the provided test set. This reduced the amount of samples in the training, validation, and test sets. Although in the original paper the main evaluation metric is the Kappa score, since the model is evaluated on the unlabeled test set, we only referred to the accuracy metric for comparison. Before training, the images go through a preprocessing stage which consists of cropping and resizing the samples. In addition, data augmentation was used to lower correlation

between features and avoid overfitting.

The method proposed by the authors falls under the category of transfer-learning methods, as it makes use of a CNN architecture pretrained on the ImageNet Dataset [?].

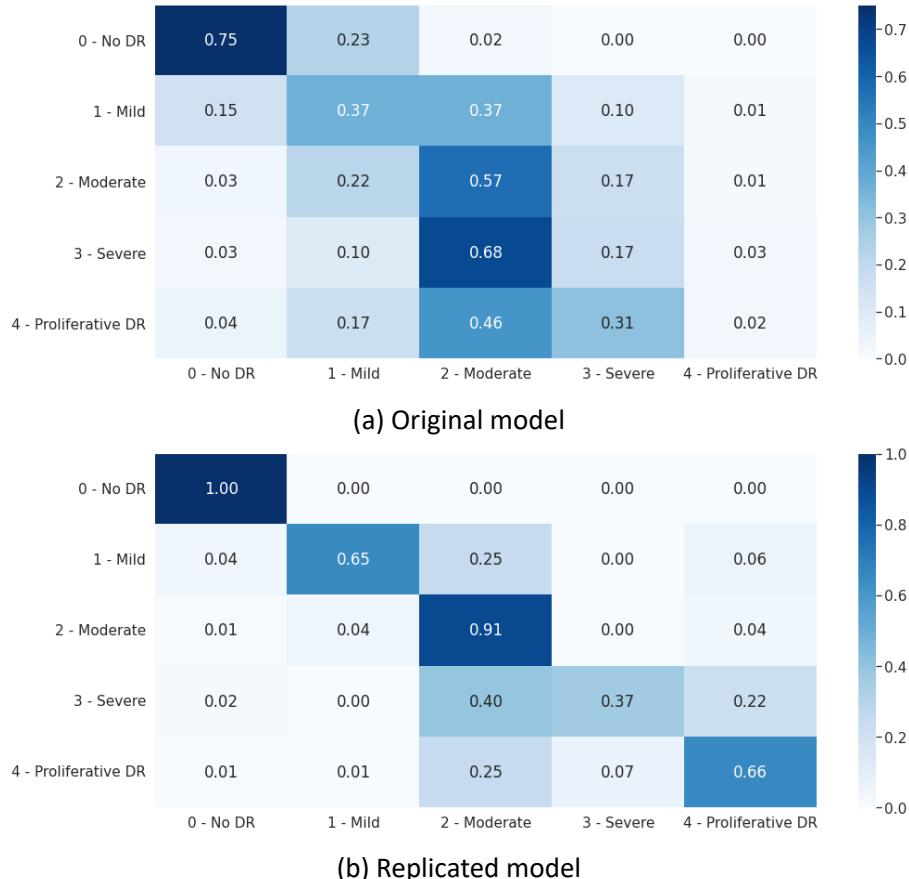


Figure 2.1: Side by side confusion matrix for model evaluation

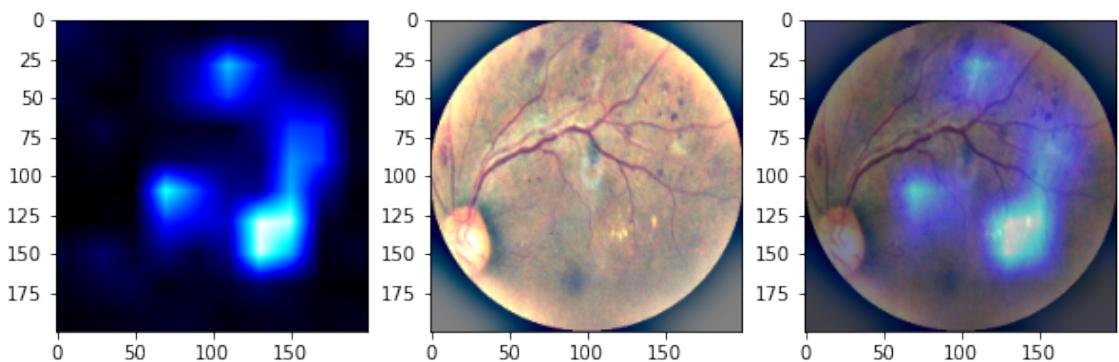


Figure 2.2: GradCAM applied to a sample image classified by the method proposed by [15], as implemented by [16]

2.1.2 Vision Transformers (ViTs)

A more recent approach to image classification comes with the rise in popularity of **Vision Transformers**. A Transformer is a deep neural network which is heavily reliant on its self-attention mechanism [18]. This type of architecture is capable of achieving a similar or better performance compared to traditional CNNs, although the two are quite often used in conjunction. Within the context of retinal image classification, however, the model of interest is **ViT** [19]. This specific architecture is regarded as a *Pure Transformer*, as it directly applies a Transformer to sequences of image patches.

The method proposed by *Wu et. al* [20] achieves an accuracy of 91.4%, specificity of 0.977, sensitivity of 0.926 and area under curve (AUC) of 0.986. The model (ViT) was trained to distinguish between the 5 traditional disease grades, and its structure is adapted from the work of *Dosovitskiy et al.* [19]. The retinal fundus images are split into non-overlapping patches and then converted into sequences through flattening and embedding operations. Such resulting sequences are then input to a series of multi-head attention layers. The model is trained on the EyePACS dataset, which undergoes preprocessing and data augmentation as usual.

2.2 Explainable AI

The recent literature on Explainable AI, specifically when applied in a medical context, highlights two main popular tools: GradCAM [14] and SIDU.

2.2.1 GradCAM

Gradient-weighted Class Activation Mapping (GradCAM) aims to highlight important features for the classification process by using class-specific gradient information [14], [11] [12]

[13]

2.3 Available Datasets

There are quite a few publicly available datasets which can be used to train DR detection models, some of which also provide grading for the disease and a risk index for developing Macular Edema. *Table 2.1* shows a summary of the characteristics of each dataset. In order for the grading information to be reliable, all images have been subject to evaluation by multiple ophthalmologists.

The first two datasets worth of mention are the *Kaggle EyePACS* [7] and the *Kaggle APTOS 2019* [6] datasets, which were both assembled in the context of challenges held by Kaggle for the detection of Diabetic Retinopathy.

Both the Kaggle datasets provide high-quality data for the model to be trained on, with the only limitation being the absence of labels for the test sets. The *EyePACS* dataset is the largest available, with over 80.000 samples distributed across 5 different disease grading levels. Uniquely from the rest, this dataset provides specimens of both eyes for each patient. Additionally, different devices were used to capture the images, contributing to the variability of the dataset. This has the potential to enhance the flexibility of the final model, allowing it to perform well on a wide variety of inputs. In order to be used for training, this dataset requires some attentive preprocessing.

Similarly, the *Aptos 2019* dataset provides DR grading across 5 different levels. The dataset was put together by Aravind Eye Hospital in India, with the hope to aid detection of Diabetic Retinopathy in rural areas. Like in the *EyePACS* dataset, the images also present noise and variability due to the different devices used for acquisition, but this time only one fundus image is available for each patient.

The *Messidor* and *Messidor-2* datasets were put together by aggregating acquisitions from different sources within the Messidor Consortium in France, within the context of a project funded by the French Ministry of Research and Defense. Specifically, the images within the dataset come from three different ophthalmologic departments, each using different equipment for the acquisition., which ensures variability in the data. Differently from the previous ones, the *Messidor* dataset only provides grading on four levels of disease, but it does provide the additional risk index for Macular Edema. However, grading on 5 levels was provided by a third party for the *Messidor-2* dataset, alongside the risk index for ME.

The *DDR* dataset provides fundus images with image-level, pixel-level and bounding-box-level annotations [8]. Additionally tho the previous ones, this dataset also provides an annotation for images that were deemed ungradable.

Finally, the *ODIR* dataset comes from another Kaggle Competition and it is structured in a different way from the rest. Differently from the rest, it does not exclusively deal with Diabetic Retinopathy, but it contains sample images related to Glaucoma, Cataract, Age related Macular Degeneration, Hypertension, Pathological Myopia, other than a general class of abnormal samples [9]. The dataset is rather small (about 5000 samples), but offers a good starting point for the development of a multi-disease classifier.

Dataset	No. Samples	Features
Kaggle EyePACS	> 80.000	Fundus images for DR detection (graded 0-4)
Kaggle APTOS 2019	5590	Fundus images for DR detection (graded 0-4)
MESSIDOR	1200	Fundus images for DR detection (graded 0-3) and assessment of ME risk (graded 0-2)
MESSIDOR-2	1748	Fundus images for DR detection (graded 0-4) and assessment of ME risk (graded 0-2)
DDR	12522	Fundus images for DR detection (graded 0-5)
ODIR	5000	Fundus images for detection of: Diabetes (D), Glaucoma (G), Cataract (C), Age related Macular Degeneration (A), Hypertension (H), Pathological Myopia (M), Other diseases/abnormalities (O)

Table 2.1: Publicly available datasets.

3 Technical Chapters (change this to something appropriate)

3.1 First Section

3.1.1 First Subsection

3.1.2 Second Subsection

4 Conclusion

4.1 Summary

Summarise what you have achieved.

4.2 Evaluation

Stand back and evaluate what you have achieved and how well you have met the objectives. Evaluate your achievements against your objectives in section [1.2](#). Demonstrate that you have tackled the project in a professional manner.

4.3 Future Work

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Appendix 1

You may have one or more appendices containing detail, bulky or reference material that is relevant though supplementary to the main text: perhaps additional specifications, tables or diagrams that would distract the reader if placed in the main part of the dissertation. Make sure that you place appropriate cross-references in the main text to direct the reader to the relevant appendices.

*Note that you should **not** include your program listings as an appendix or appendices.*
You should submit one copy of such bulky text as a separate item, perhaps on a disk.

Appendix 2 – User guide

If you produced software that is intended for others to use, or that others may wish to extend/improve, then a user guide and an installation guide appendices are **essential**.

Appendix 3 – Installation guide

If you produced software that is intended for others to use, or that others may wish to extend/improve, then a user guide and an installation guide appendices are **essential**.