1.INTRODUCTION.

Diabetic retinopathy (die-Uh-BET-ik ret-NOP-uh-thee) is a diabetes complication affects eyes. It's causes by damage to the blood vessels of the lightsensitive tissue at the back of the eye (retina). At first, diabetic retinopathy might causes no symptoms or only mild vision problems.

2.LITERATURE SURVEY

Diabetes is a globally prevalent disease that can causevisiblemicro vascular complications such as diabetic retinopathyandmacular in the human eye retina, the images of whicharetodayused for manual disease screening and diagnosis. Thisintensive task could greatly benefit fromautomatic detectionusing deep learning technique. Here we present a deeplearningsystem that identifies referable diabetic retinopathy

comparably or better than presented in the previousstudies, although we use only a small fraction of images (<1/4) intraining but are aided with higher image resolutions. Wealsoprovide novel results for five different screening andclinical

grading systems for diabetic retinopathy and macular

classification including state-of-the-art results for accuratelyclassifying images according to clinical five-grade diabeticretinopathy and for the first time for the four-grade diabeticmacular scales. These results suggest that a deeplearningsystem could increase the cost-effectiveness of screeninganddiagnosis, while attaining higher than recommendedperformance, and that the system could be appliedinclinical

examinations requiring finer grading.

Introduction

Diabetic retinopathy is the most common microvascular complication in diabetes, for the screeningofwhich the retinal imaging is the most widely usedmethod due to its high sensitivity in detectingretinopathy. The evaluation of the severity anddegreeofretinopathy associated with a person havingdiabetesiscurrently performed by medical experts basedonthefundus or retinal images of the patient's eyes. Asthenumber of patients with diabetes is rapidly increasing, the number of retinal images produced by thescreeningprogrammes will also increase, which in turnintroducesa large intensive burden on the medical expertsaswell

as cost to the healthcare services. This couldbealleviated with an automated systemeither assupportfor medical experts' work or as full diagnosistool. Thereare two recent studies that have investigatedtheuseofdeep learning systems in automated detectionof

diabetic retinopathy. Both show that an automatedsystem, based on the deep learning artificial neural

network approach, can achieve high sensitivitywithhighspecificity in detecting the referable diabeticretinopathy, defined as moderate or worse diabetic retinopathy. There are also other referable eye complicationsthathave recently been investigated with this approach, suchas diabetic macular and possible glaucomaandage- related macular degeneration. Methods

Original fundus image dataset

The research of present study was done incollaborationwith Digifundus Ltd, an ISO 9001:2015 certifiedproviderof diabetic retinopathy screening and monitoringservices in Finland. Digifundus Ltd providedanon-open, anonymized retinal image dataset of patientswithdiabetes, including 41122 graded retinal colour imagesfrom 14624 patients. The images were takenwithCanon CR2 retinal camera after inducing withtropicamide 5 mg/ml eye drops. Two 45 degreecolourfundus photographs, centered on fovea andopticdiscwere taken from the patient's both eyes. Theoutputimages were of variable resolutions, rangingfrom3888 × 2592 to 5184 × 3456 pixels. The present study is a methodological study withanonymized medical data and without any interventionin the integrity of a person such as contact withaperson. In Finnish law this is not consideredasamedical study requiring approval by an ethicscommitteeor a written consent of a person. Retinal image grading systems and gradabilityEach of the retinal images had been gradedwithrespectto three different criteria, (i) diabetic retinopathy, (ii)macular edema, and (iii) gradability. Imagesaregradedwith the proposed international clinical diabeticretinopathy and macular edema disease severityscalesdenoted later as PIRC and PIMEC, respectively. Theimage gradability is a two-stage system, whichconsiders an image to be either gradable or not. All

personnel participating in retinopathy assessment had

over 10 years' experience in diabetic retinopathygrading.Retinal images with no lesions or mild diabeticlesionswere graded by an optometrist and an M.D. trainedforretinopathy grading. All images with moderateor worsechanges were graded by two ophthalmologist bothwithmore than 10 years of experience in gradingfundusimages. If there was a disagreement in grading, suchanimage was not included in this study. PIRC and PIMEC grades were further usedtoobtainadditional three types of grading systems: (i) abinarysystem ofnonreferable /referable diabetic

retinopathy (NRDR/RDR), (ii) a binary systemofnonreferable /referable diabetic macular

edema (NRDME/RDME), and (iii) three-classsystemofungradable/NRDR/RDR. The NRDR/RDRsystemconsiders the cases with no diabetic retinopathyandmild diabetic retinopathy as nonreferable diabeticretinopathy, and the cases with moderate or worsediabetic retinopathy as referable diabetic retinopathy. This system has been used in recent works investigatingautomated detection of diabetic retinopathy. TheNRDME/RDME system here is defined suchthat theabsence of macular edema is defined as nonreferablediabetic macular edema and any level of macular edemaas referable diabetic macular edema. Note that onlythegradable images were graded for diabetic retinopathyand macular edema. Ungradable images wereincludedin a single task, in combination with referablediabeticretinopathy classification, which constitutesthegradingsystem QRDR, in which each image is consideredtobeeither ungradable, depicting nonreferable diabeticretinopathy, or depicting referable diabetic retinopathy

(ungradable/NRDR/RDR). Image preprocessing and dataset divisionIn the model training and subsequent primaryvalidation, we used preprocessed versions of the original images.The preprocessing consisted of image croppingfollowed by resizing. Each image was croppedtoasquare shape which included the most tightly containedcircular area of fundus. The procedure removedmostofthe black borders and all of the patient relatedannotations from the image data. Each of thecroppedimages were then resized to five different standardinputimage sizes of 256 × 256, 299 × 299, 512 × 512, 1024 × 1024, and 2095 × 2095 pixels. The largest imagesize was the smallest native resolution of theretinal

cameras after the preprocessing steps. Herethecreation of multiple resolutions was done for thepurposes of analyzing the effect of the input imageresolution on the classification performance. The obtained processed datasets were dividedintothree sets:training ,tuning , andprimary validationsetinthe 70%, 10% and 20% proportions of the wholeimagedataset, respectively, separately for each of thegradingsystems used in the experiments. In the divisionperaparticular grading system, the different setsweretohave similar grade distributions, and that thedatasetdata per patient to not reside in multiple but onlyinoneof the three sets (of training, tuning, and primaryvalidation), in order to prevent the possibility of

obtaining over-optimistic results due to datamemorization. Table 1 shows the statistics of the

resulting divisions that were used in the experiments. Note that the grade distributions across thedifferentsets were similar, with respect to each gradingsystem, for example, when we consider the NRDR/RDR-system, the proportion of images associated with referablediabetic retinopathy in the training, tuning andprimaryvalidation set 44%, 43.9% and 43.4%, respectively. Results

In the binary classification tasks, i.e. NRDR/RDRandNRDME/RDME, our algorithmachieved the best resultsusing the largest 2095 × 2095 pixels input imagesize. Inthe NRDR/RDR classification on our primary validationset having 7118 images, our algorithmachievedthesensitivity of 0.896 (with 95% CI: 0.885–0.907) andspecificity 0.974 (with 95% CI: 0.969–979) andAUCof0.987 (with 95% CI: 0.984–0.989). Our model

performance was evaluated at the operatingpoint wherethe tuning set achieved 0.900 sensitivity, inasimilarmanner to Tinget al . while Gulshanet al . hadtwooperating points namely at a high specificity (0.980)point and at a high sensitivity (0.975) point. InTablewepresent the AUC values of our model, alongwiththeAUC values reported by Gulshanet al . andTinget al . TheTwo other recent studies, Krauseet al . andGuanet al

also explored the NRDR/RDR classification, but astheydo not report res ults close to the 0.900 sensitivitypoint, References

1. Marshall, S. M. & Flyvbjerg, A. Prevention and early detectionof

vascular complications of diabetes.BMJ. 333(7566), 475–480(2006).

2. Hutchinson, A.et al . Effectiveness of screening and monitoringtestsfor diabetic retinopathy–a systematic review.Diabet Med. 17(7), 495–506 (2000). 3. Taylor, R. & Batey, D.Handbook of Retinal Screening in Diabetes:

Diagnosis and Management . Wiley (2012). 4. Gulshan, V.et al . Development and Validation of a Deep LearningAlgorithm for Detection of Diabetic Retinopathy in Retinal FundusPhotographs.JAMA. 316(22), 2402–2410 (2016). 5. Ting, D. S. W.et al . Development and Validation of a

DeepLearningSystem for Diabetic Retinopathy and Related Eye Diseases UsingRetinal Images From Multiethnic Populations With

Diabetes.JAMA. 318(22), 2211–2223 (2017). 6. Wilkinson, C. P.et al . Proposed international clinical diabeticretinopathy and diabetic macular edema disease severity

scales.Ophthalmology. 110(9), 1677–1682 (2003). 7. Summanen, P.et al . Update on Current Care Guideline: Diabeticretinopathy.Duodecim. 131(9), 893–894 (2015)

8. Krause, J.et al . Grader Variability and the Importance of ReferenceStandards for Evaluating Machine Learning Models for DiabeticRetinopathy.Ophthalmology. 125(8), 1264–1272 (2018). 9. Guan, M. Y., Gulshan, V., Dai, A. M. & Hinton, G. E. Who SaidWhat:

Modeling Individual Labelers Improves Classification.arXiv e-prints., https://ui.adsabs.harvard.edu/\#abs/2017arXiv170308774G. (Accessed March 01, 2017). 10. Wang, F., Casalino, L. P. & Khullar, D. Deep Learning inMedicine-Promise, Progress, and Challenges.JAMA Intern Med . 11. Medical Research

Act, https://www.finlex.fi/en/laki/kaannokset/1999/en19990488_20100794.pdf

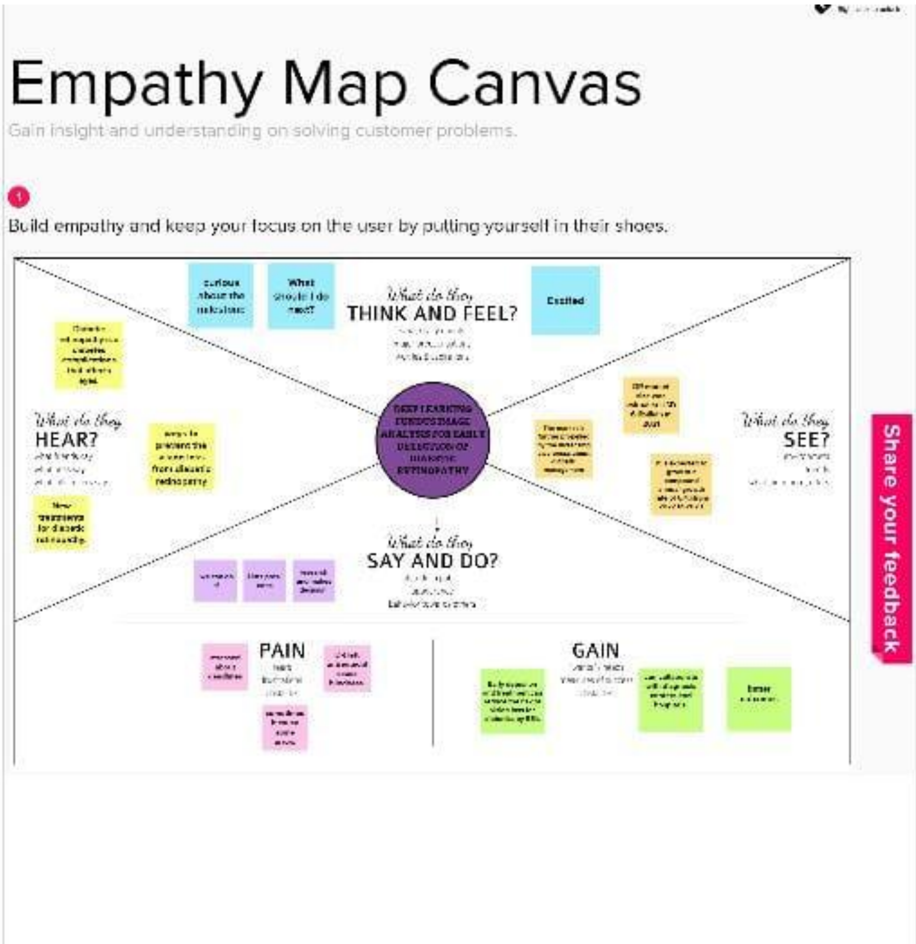
12. Goodfellow, I., Bengio, Y. & Courville, A. Deep Learning. MITPress

13. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. & Wojna, Z. Rethinking the Inception Architecture for Computer Vision.arXive- prints . 2015, https://ui.adsabs.harvard.edu/\#abs/2015arXiv151200567S14. Russakovsky, O.et al . ImageNet Large Scale Visual

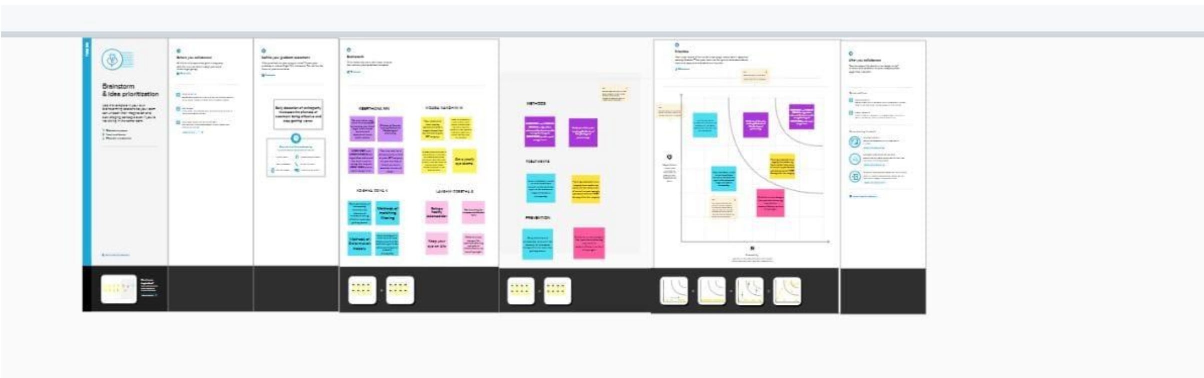
Recognition Challenge. 15. Decencière, E.et al .Feedback on a publicly distributedimagedatabase: The Messidor database . Vol 02014

3.IDEATION & PROPOSED SOLUTION:

3.1 EMPATHY MAP CANVAS



3.2 IDEATION & BRAINSTORMING



3.3 PROPOSED SOLUTION:

Project Design Phase-I
Proposed Solution

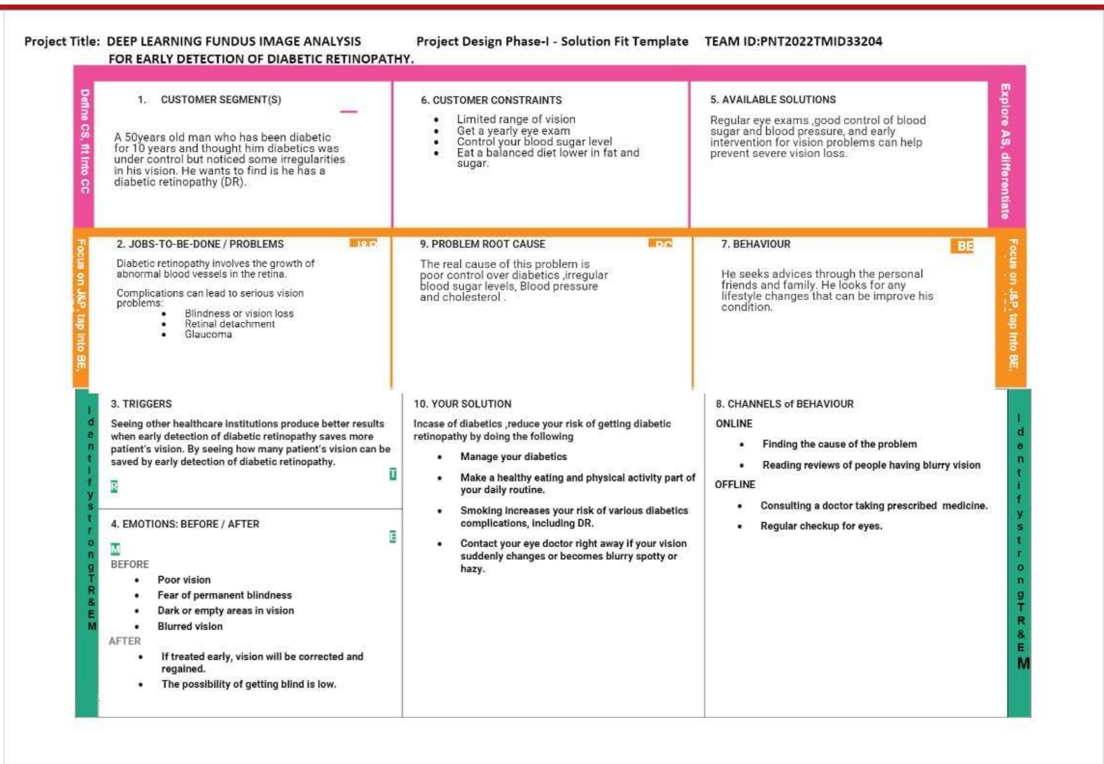
Date	19 September 2022
Team ID	PNT2022TMID33204
Project Name	DEEP LEARNING FUNDUS IMAGE ANALYSIS FOR EARLY DETECTION OF DIABETIC RETINOPATHY.
Maximum Marks	2 Marks

Proposed Solution Template:

Project team shall fill the following information in proposed solution template.

S.No.	Parameter	Description
•	Problem Statement (Problem to be solved)	• Diabetic retinopathy is a leading cause of vision loss globally.Early detection of retinopathy increases the chances of treatment being effective and stop getting worse.
•	Idea / Solution description	• You can reduce your of developing DR by keeping your blood sugar levels,blood pressure and cholesterol levels under control andPay attention to the vision changes.
•	Novelty / Uniqueness	• IDX-DR is an AI diagnostic system that autonomously diagnosis patients for diabetic retinopathy. • No need for specialist overread or telemedicine call backs. • A Simple user interface. • customised workflow integration solution.
•	Social Impact / Customer Satisfaction	• Helps in preventing the loss of visibility to the needed through CSR activities or through healthcare camps.
•	Business Model (Revenue Model)	• Can collaborate with diagnosis centers and hospitals and government for health awareness camps.
•	Scalability of the Solution	• Agreement was high ,and exams containing more than minimal DR were detected.IDX-DR analyzes images for signs of diabetic retinopathy is accurate and providing results in 30seconds.

3.4 PROBLEM SOLUTION FIT:



Project Title: DEEP LEARNING FUNDUS IMAGE ANALYSIS FOR EARLY DETECTION OF DIABETIC RETINOPATHY. **Project Design Phase-I - Solution Fit Template** **TEAM ID:PNT2022TMID33204**

Define CS, fit into CC

1. CUSTOMER SEGMENT(S)

A 50years old man who has been diabetic for 10 years and thought him diabetics was under control but noticed some irregularities in his vision. He wants to find is he has a diabetic retinopathy (DR).

6. CUSTOMER CONSTRAINTS

- Limited range of vision
- Get a yearly eye exam
- Control your blood sugar level
- Eat a balanced diet lower in fat and sugar.

5. AVAILABLE SOLUTIONS

Regular eye exams ,good control of blood sugar and blood pressure, and early intervention for vision problems can help prevent severe vision loss.

Explore AS, differentiate

Focus on J&P, tap into BE,

2. JOBS-TO-BE-DONE / PROBLEMS

Diabetic retinopathy involves the growth of abnormal blood vessels in the retina.

Complications can lead to serious vision problems:

- Blindness or vision loss
- Retinal detachment
- Glaucoma

9. PROBLEM ROOT CAUSE

The real cause of this problem is poor control over diabetics ,irregular blood sugar levels, Blood pressure and cholesterol .

7. BEHAVIOUR BE

He seeks advices through the personal friends and family. He looks for any lifestyle changes that can be improve his condition.

Focus on J&P, tap into BE,

Identify strong TR & EM

3. TRIGGERS

Seeing other healthcare institutions produce better results when early detection of diabetic retinopathy saves more patient's vision. By seeing how many patient's vision can be saved by early detection of diabetic retinopathy.

TR

4. EMOTIONS: BEFORE / AFTER

EM

BEFORE

- Poor vision
- Fear of permanent blindness
- Dark or empty areas in vision
- Blurred vision

AFTER

- If treated early, vision will be corrected and regained.
- The possibility of getting blind is low.

10. YOUR SOLUTION

Incase of diabetics ,reduce your risk of getting diabetic retinopathy by doing the following

- Manage your diabetics
- Make a healthy eating and physical activity part of your daily routine.
- Smoking increases your risk of various diabetics complications, including DR.
- Contact your eye doctor right away if your vision suddenly changes or becomes blurry spotty or hazy.

8. CHANNELS of BEHAVIOUR

ONLINE

- Finding the cause of the problem
- Reading reviews of people having blurry vision

OFFLINE

- Consulting a doctor taking prescribed medicine.
- Regular checkup for eyes.

Identify strong TR & EM

4 REQUIRMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT &

4.2 NON-FUNCTIONAL REQUIREMENTS

Project Design Phase-II
Solution Requirements (Functional & Non-functional)

Date	03 October 2022
Team ID	PNT2022TMID33204
Project Name	Deep learning fundus image analysis for early detection of Diabetic retinopathy.
Maximum Marks	4 Marks

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	Identifying and selecting dataset	The appropriate dataset to enhance the model's performance is necessary to select.
FR-2	Invitation and information	Invite the full cohort for screening ,supplying information tailored appropriately for different groups to enable informed choice to participate.
FR-3	Training	It is required to import the libraries needed for training the model.
FR-4	Diagnosis	Diagnosis true cases and identify the false solution.
FR-5	Testing	Conduct screening tests with different data to test if the model is trained well to predict the medical condition.
FR-6	Reporting and treatment	Report the outcomes to identify false negative and improve effectiveness of the screening program. The testing of the model helps us to identify the appropriate treatment.

Non-functional Requirements:

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Users with basic understanding of the medical condition and computer knowledge can operate the system.User friendly interface that can be accessed with ease by users.
NFR-2	**Security**	Deep learning AI can be more precise around sensitive organs and tissues ,reduce blood loss,risk of infection,and pain during detection.
NFR-3	**Reliability**	There is a chance of hardware failure or false positives when the testing data is more different than the training dataset. Permission granted only by the administrator of the system.
NFR-4	**Performance**	If the system update fails or bugs in the code even though the system can roll back to its initial state.The performance of the model is meant to give speed results for the patients.
NFR-5	**Availability**	The treatement should be available at low cost so that everyone with DR can find it beneficial.
NFR-6	**Scalability**	By processing more datasets for the reference of DR detection.

5.PROJECT DESIGN

5.1 DATA FLOW DIAGRAMS &

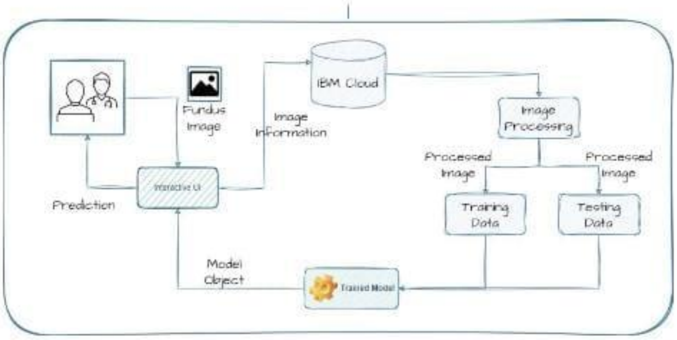
5.2 USER STORIES

Project Design Phase-II
Data Flow Diagram &User Stories

Date	03October 2022
Team ID	PNT2022TMID33204
Project Name	Deep Learning Fundus Image Analysis for Early Detection of Diabetic Retinopathy
Maximum Marks	4 Marks

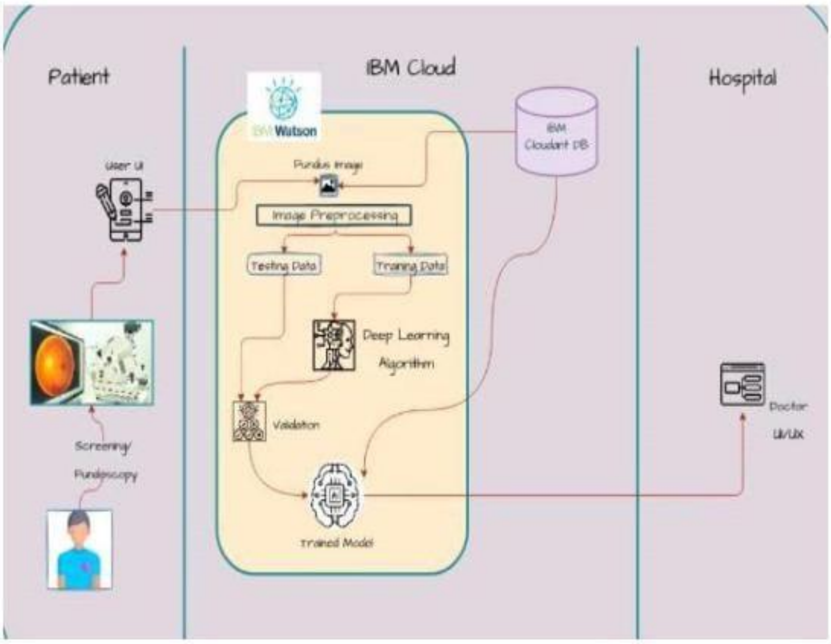
Data Flow Diagrams:

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



5.3 SOLUTION & TECHNICAL ARCHITECTURE:

TECHNOLOGY ARCHITECTURE:

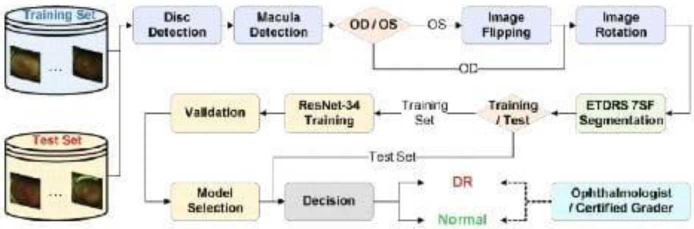


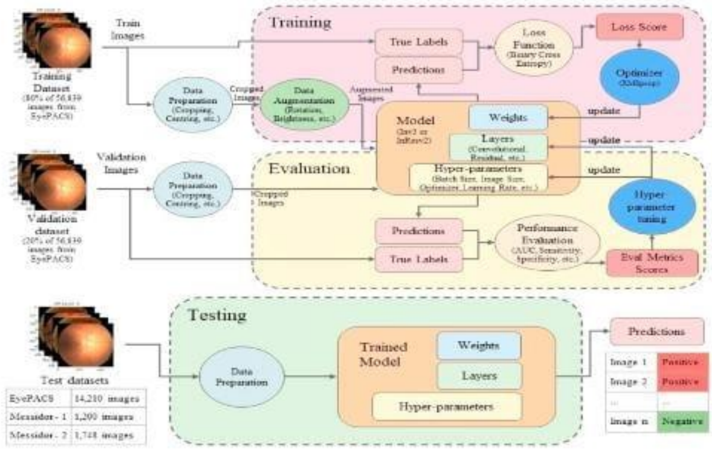
PROJECT DESIGN PHASE –1

SOLUTION ARCHITECTURE

DATE	17 OCTOBER 22
TEAM ID	PNT2022TMID33204
PROJECT NAME	DEEP LEARNING FUNDUS IMAGE ANALYSIS FOR EARLY DETECTION OF DIABETIC RETINOPATHY.
MAXIMUM MARKS	4 MARKS

SOLUTION ARCHITECTURE:





6. PROJECT PLANNING & SCHEDULING:

6.1 SPRINT PLANNING & ESTIMATION:

7. CODING & SOLUTIONING:

```python
from cloudant.client import cloudant
client = cloudant.iam("d0963b0d-6a01-4b4d-ac1b-78ccef67e303-bluemix","vRzNCfpRbo2Bf4UidNaXBfP-vWRHGp5vr9at0BfDs7
my_database = client.create_database('diabetic-retinopathy')
```

8. ADVANTAGE

Early detection and timely treatment having been show to prevent visual loss and blindness in patints with retinal complication of diabetes

DISADVANTAGES

High capital setup costs

Need to provide regular training for grader

9.conclusion

Diabetic retiopathy is now recognized to be an inflammatory neurovascular complication of the systemic disease with neuronal injury preceding the current clinical microvascular the inflammatory tissue injury concurrent in other organs.