Deep Learning Fundus Image Analysis For Early Detection Of Diabetic Retinopathy

Professional Readiness for Innovation, Employability and Entrepreneurship

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CONTENTS

1. INTRODUCTION

PROJECT OVERVIEW

The retina of the human eye can develop visible microvascular consequences from diabetes, including diabetic retinopathy and macular edema, the images of which are being employed for manual disease screening and diagnosis. Deep learning-based automatic detection for this labor-intensive task could be quite helpful. Although we only employ a tiny portion of photos in training, greater image resolutions help our deep learning system identify referable diabetic retinopathy comparably or better than given in the prior studies. In addition, we present cutting-edge results for appropriately classification of images as per medical five-grade diabetic retinopathy scales and for the first time for the four-grade diabetic macular edema scales. These results cover five different screening and clinical grading systems for the classification of diabetic retinopathy and macular edema. These findings imply that a deep learning system could improve screening and diagnostic cost-effectiveness while delivering performance above required levels, and that the technology could be used in clinical exams demanding finer grading.

PURPOSE

The most prominent microvascular consequence of diabetes is diabetic retinopathy, and retinal imaging is the most used tool for diagnosing because of its great sensitivity. On the basis of the fundus or retinal images of the patient's eyes, medical professionals today assess the severity and degree of retinopathy associated with a person having diabetes. As the number of diabetic patients rises quickly, more retinal images will be generated by screening programmes, which places a heavy workload on medical professionals and raises the cost of healthcare services. An automation system could help with this both as a mechanism for complete diagnosis or as a complement for the work of scientific professionals. The application of deep learning models for automated identification of diabetic retinopathy has been examined in two recent publications. Both demonstrate that a deep learning artificial neural network-based automated system can diagnose pertaining diabetic retinopathy, which is classified as moderate or worse eye disease, with significant sensitivity and specificity. Other related eye disorders, such as diabetic macular edema, potential glaucoma, and age-related macular degeneration, have also recently been studied with this method.

An automated system must be able to categorise retinal pictures using severity scales that are clinically applicable, such as the scales for diabetic retinopathy and macular edema that are being suggested internationally and that are being used in Finland. Recent studies for the former example of the diabetic retinopathy scale may be found in the literature, however no studies have been conducted yet to categorise macular alterations with the later scale. The enormous number of annotated photos required for the model to learn is regarded to be a significant impediment to the deeper learning system's wider and more successful application.

The goal in this project is to classify macular edema and diabetic retinopathy using five distinct classification schemes. We provide the most recent findings for the biologically meaningful five categories of classification, as well as the initial four grade macular edema classification, in addition to the prior research of the referable diabetic retinopathy classification system. Additionally, we outline the preprocessing and regularisation processes that must be performed on the data for the deep learning system to perform properly and carefully examine how the scale and quantity of photos used in training affect the system's performance.

2. LITERATURE SURVEY

EXISTING PROBLEM

A diabetes condition that impacts the eyes is diabetic retinopathy. Damage to the blood vessels in the light-sensitive tissue at the back of the eye is what causes it (retina). Initially, diabetic retinopathy may not manifest any symptoms or may only result in minor vision issues. Deep learning is a key component in ophthalmology to diagnose critical disorders like diabetic retinopathy (DR). Diabetic retinopathy is a common disease that diabetic patients are diagnosed with. The analyst is responsible for manually detecting exudates, which takes time.

REFERENCES

S.NO	AUTHOR	TITLE	OBJECTIVE
1.	Xiaogang Li et al. (2017)	Convolutional neural networks based transfer learning for diabetic retinopathy fundus image classification [1]	To implement transfer learning based on CNNs for diabetic retinopathy fundus picture classification. On 1014 and 1200 fundus pictures from the two publicly accessible DR1 and MESSIDOR databases, experiments are conducted.
2.	Saboora Mohammadian et al. (2017)	Comparative Study of Fine-Tuning of Pre-Trained Convolutional	In this study, pre-trained convolutional neural networks are used to automatically diagnose diabetic retinopathy. To circumvent the resource- and time-intensive training procedures required to

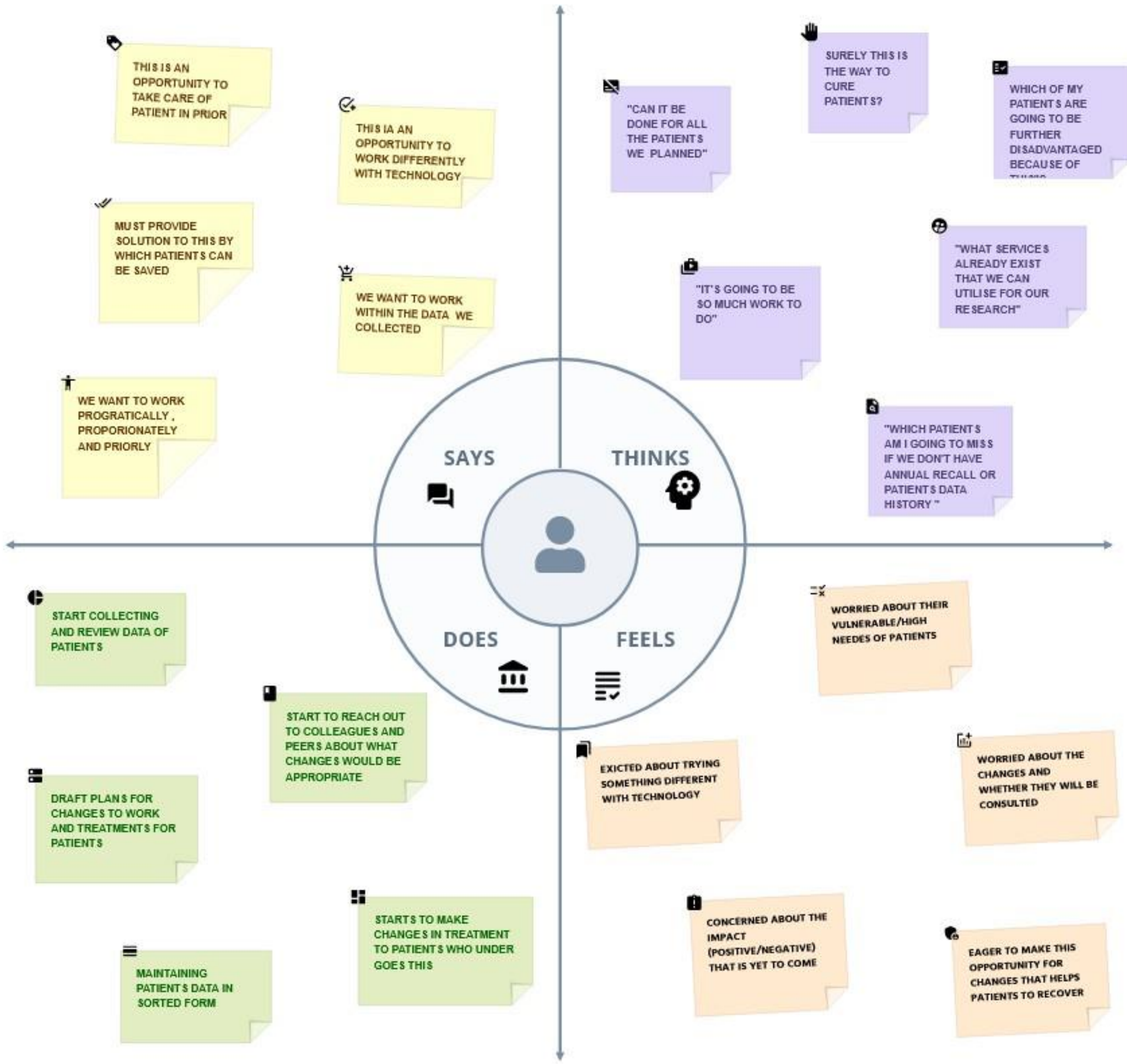
		Neural Networks for Diabetic Retinopathy Screening [2]	create a convolutional neural network from scratch, pre-trained networks are used.
3.	ParhamKhojasteh et al. (2019)	Exudate detection in fundus images using deeply-learnable features [3]	This study looked into various deep learning techniques in order to increase sensitivity and specificity . In this research, several deep learning techniques, including CNNs, pre- trained Residual Networks (ResNet-50), and Discriminative Restricted Boltzmann Machines, were evaluated with both supervised and unsupervised classifiers to improve the performance of autonomous exudate identification.
4.	Md Robiulislam et al. (2019)	Applying supervised contrastive learning for the detection of diabetic retinopathy and its severity levels from fundus images [4]	In this research a SCL approach, a two-stage training method with supervised contrastive loss function, to identify the DR and its severity stages from fundus images (FIs) using the "APTOS 2019 Blindness Detection" dataset was proposed. Experiments were carried out to further validate the performance of the model using the "Messidor-2" dataset.

5.	Muhammad Mateen et al. (2019)	Exudate Detection for Diabetic Retinopathy Using Pretrained Convolutional Neural Networks [5]	To detect exudate using a pretrained convolutional neural network (CNN)- based framework. In the suggested method, data preprocessing is done initially to standardise exudate patches.
6.	Laxmi Math et al. (2020)	Adaptive machine learning classification for diabetic retinopathy [6]	To develop a segment- based learning method for detecting diabetic retinopathy that simultaneously learns classifiers and features from the data and makes considerable progress in identifying the visual manifestations of the disease and its internal lesions.
7.	V. Deepa et al. (2022)	Automated grading of diabetic retinopathy using CNN with hierarchical clustering of image patches by siamese network [7]	To develop a feature extraction technique for DR grading based on deep learning convolutional neural network (CNN) using discriminative multi-sized patches.

8.	Mohamed Abdou BERBAR et al. (2022)	Diabetic Retinopathy Detection and Grading using Deep learning [8]	To provide a novel enhancing method to improve the quality of fundus images. Additionally, it suggests two convolutional neural network (CNN) model topologies. The first one divides DR images into two categories: normal and pathological. the second CNN architecture to categorise DR severity levels.
9.	AliKarsaz et al. (2022)	A modified convolutional neural network architecture for diabetic retinopathy screening using SVDD [9]	This study suggests automated approaches for diagnosing diabetic retinopathy to speed up examinations and assist doctors. Due to the retinal pictures' similar feature maps and slight variations in spatial domain, this method may not be the best for detecting diabetic retinopathy. Therefore, the classifier in this research proposes a new high level picture understanding employing a modified CNN architecture combined with a modified SVDD.
10.	Mohamed A. Berbar et al. (2022)	Features extraction using encoded local binary pattern for detection and grading diabetic retinopathy [10]	This study is to identify diabetic retinopathy in fundus pictures and assess the disease's severity with no lesion segmentation.

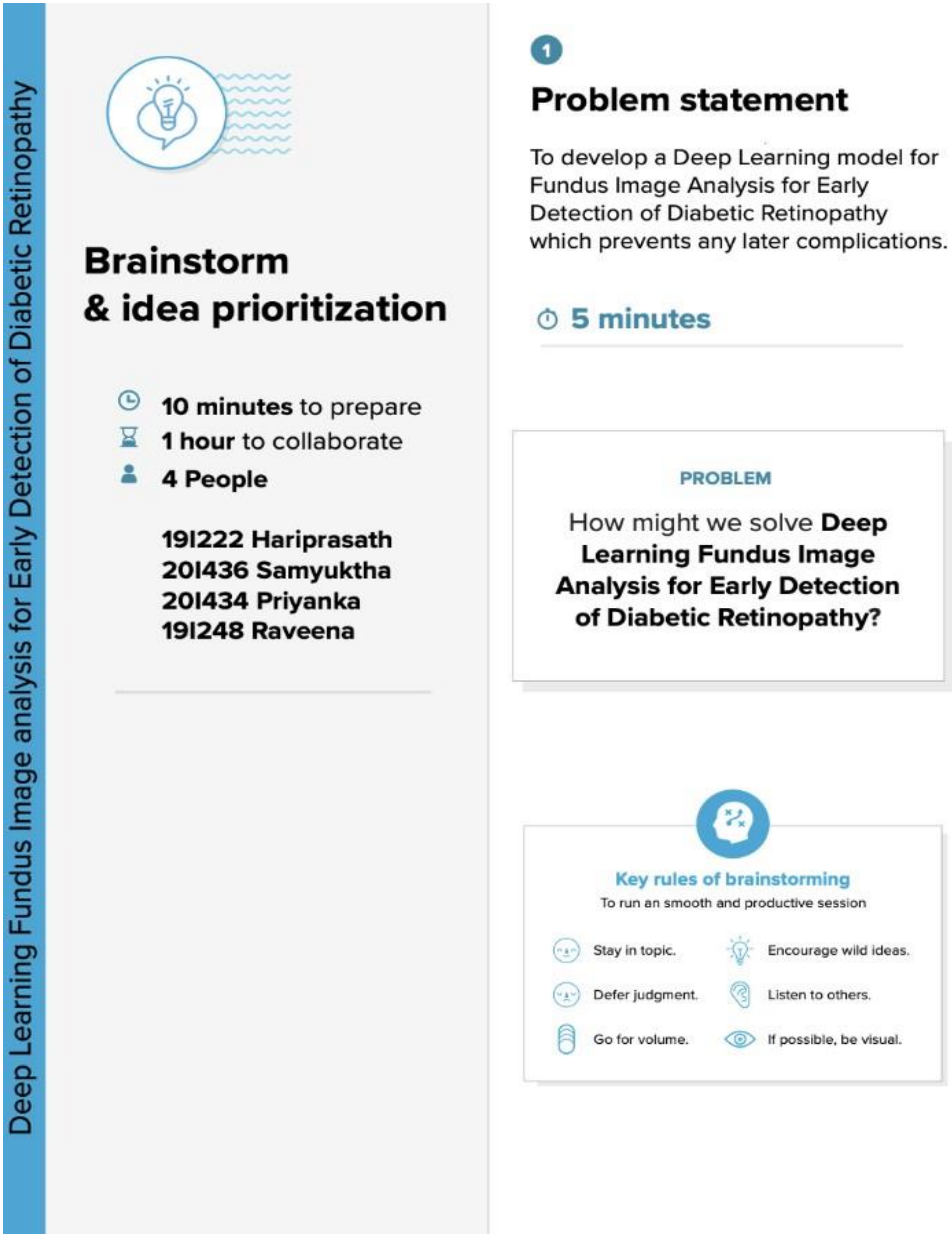
3. IDEATION & PROPOSED SOLUTION

EMPATHY MAP CANVAS



GAINS	PAINS
PATIENT RECOVERY	MISSING PATIENT DATA
NEW TECHNOLOGY EVOLUTION	CONVENCING PATIENTS TO UNDER GO NEW TREMENT
NEXT LEVEL OF MEDICAL RESEARCH	SECURITY FOR PATIENT DATA'S
OBTAINED CURABLE MEDICINE	STRUGGLES/CHALLENGES

IDEATION & BRAINSTORMING



2

Brainstorm

Write down any ideas that come to mind that address your problem statement.

10 minutes

thenmozhi

- Extract features from well-known pre-trained deep learning model
- Pre-trained models, in order to detect exudates from diabetic retinopathy, and then perform performance evaluation on the models.
- With the aid of exudates that have been extracted, the system that will be developed.
- segment-based learning method that simultaneously learns classifiers and features from the data

sharmila

- The exudates are recognised based on their characteristics, such as colour, texture, shape, and size.
- Diabetic retinopathy is a common disease that diabetic patients are diagnosed with.
- Sort the diabetic retinopathy into mild, moderate, severe, or proliferative categories..
- Damage to the blood vessels in the light-sensitive tissue at the back of the eye is what causes it (retina)

sasi priya

- A diabetes condition that impacts the eyes is diabetic retinopathy.
- identify diabetic retinopathy in fundus pictures and assess the disease severity.
- Automated approaches for diagnosing diabetic retinopathy to speed up examinations and assist doctors.
- It conducts the classification of diabetic and normal macular edema.

mohammed althaf,kiruthika

- Initially, diabetic retinopathy may not manifest any symptoms or may only result in minor vision issues.
- Deep learning is a key component in ophthalmology to diagnose critical disorders like diabetic retinopathy (DR).
- The analyst is responsible for manually detecting exudates, which takes time.
- Color fundus retinal pictures should be processed to look for diabetic retinopathy.

3

Group ideas

Take turns sharing your ideas while clustering similar or related notes as you go. In the last 10 minutes, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.

20 minutes

Features & Extraction

- Identify characteristics in a well-known, previously trained deep learning model.
- In addition to a complicated grading system, the manual diagnosis of diabetic retinopathy (DR) through colour fundus pictures necessitates trained doctors to recognise the presence and relevance of numerous tiny characteristics.
- Remove the optic disc out of the picture using the properties of the same and feed the picture to the same ML model that was developed.
- The empirical proof can be given by removing the optical disc and feeding the picture to the two models and predicting the output.

Model

- To detect exudate using a pretrained convolutional neural network (CNN)-based framework.
- A two-stage training method with supervised contrastive loss function, to identify the DR.
- The existing system uses RESNET-50 which is pre-trained and is highly complex.
- Multiple simple algorithms work together to complement and augment each other

Classification

- The current model used was a spinoff of CNN with varying number of layers.
- A Convolutional Neural Network, also known as CNN or ConvNet, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image.
- A hybrid machine learning model that takes the pictures as the input and classifies the exudates based on grades that is 0-5.
- The optical disc in the picture is proving to be an impediment in the prediction process.

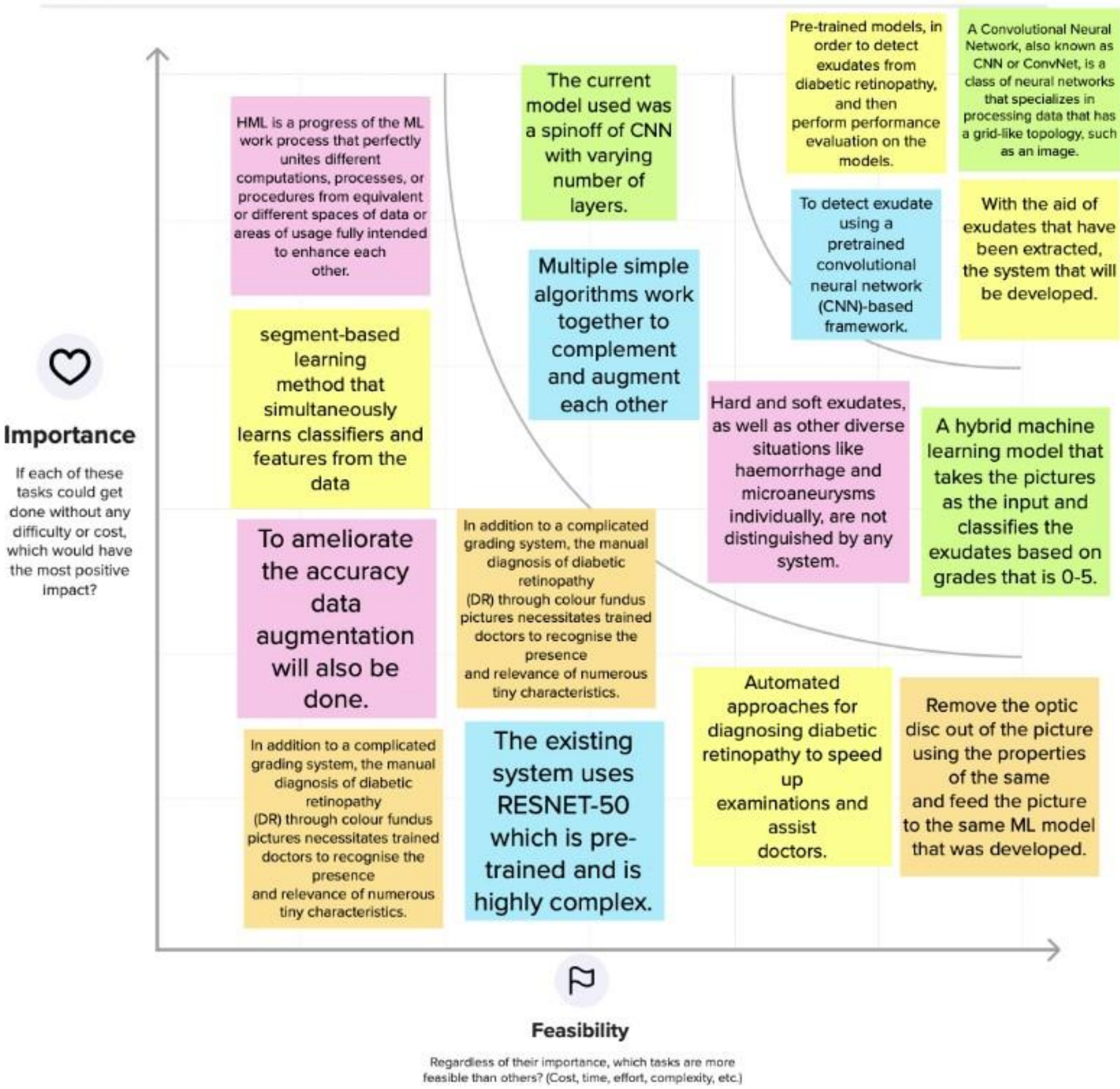
Approach

- Hard and soft exudates, as well as other diverse situations like haemorrhage and microaneurysms individually, are not distinguished by any system.
- HML is a progress of the ML work process that perfectly unites different computations, processes, or procedures from equivalent or different spaces of data or areas of usage fully intended to enhance each other.
- As no single cap fits all heads, no single ML procedure is appropriate for all issue
- To ameliorate the accuracy data augmentation will also be done.

Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

⏱ 20 minutes



PROPOSED SOLUTION

S.No	Parameter	Description
1.	Problem Statement (Problem to be solved)	Early Detection of Diabetic Retinopathy using Deep Learning
2.	Idea/ Solution description	By the use of a hybrid model that perfectly unites different computations, processes, or procedures from equivalent or different spaces of data or areas of usage fully intended to enhance each other.
3.	Novelty/ Uniqueness	Hard and soft exudates, as well as other diverse situations like haemorrhage and microaneurysms individually, are not distinguished by any system. Models like RESNET-50, Xception etc., which are pre-trained and are highly complex.
4.	Social Impact/ Customer Satisfaction	●Early detection of the disease ● Efficient prediction mechanism with faster results. ●Easy to use and understand
5.	Business Model (Revenue Model)	●Data analytics ● Statistics ●Future prediction
6.	Scalability of the Solution	The model is scalable from the architecture and dataset training perspective. We can train huge amounts of image data by converting them into .npy / .npz file format which would facilitate easy storing, retrieving and processing.

PROBLEM SOLUTION FIT

Define CS, fit into CC

1. CUSTOMER SEGMENT(S) — CS

Who is your customer?
i.e. working parents of 0-5 y.o. kids

The early detection is important for the diabetic patients as diabetic retinopathy is irreversible. The Diabetic retinopathy can be detected using the fundus image of the patient and can be stored in the database.This is more useful than the manual examination

6. CUSTOMER CONSTRAINTS — CC

What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices.

The diabetic retinopathy does not have any specific symptoms so they fail to notice the illness. Many people do not know about diabetic retinopathy and its adverse reaction.

5. AVAILABLE SOLUTIONS — AS

Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros & cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking

Laser treatment to treat the growth of new blood vessels at the back of the eye (retina) in cases of proliferative diabetic retinopathy, and to stabilize some cases of maculopathy. eye injections - to treat severe maculopathy that's threatening your sight.

Explore AS, differentiate

Focus on J&P, tap into BE, understand RC

2. JOBS-TO-BE-DONE / PROBLEMS — J&P

Which jobs-to-be-done (or problems) do you address for your customers?
There could be more than one; explore different sides.

The problem is once the diabetic retinopathy is severe, it cannot be done. And the severity of diabetic retinopathy results in serious eye illness and also results in losing vision. So, early detection is important if the patient has diabetes.

9. PROBLEM ROOT CAUSE — RC

What is the real reason that this problem exists?
What is the back story behind the need to do this job?
i.e. customers have to do it because of the change in regulations.

Diabetic retinopathy is caused by changes in the blood vessels of the retina, the light-sensitive layer of tissue at the back of the inner eye. In some people with diabetic retinopathy, the blood vessels in the retina may swell and leak fluid. In others, abnormal new blood vessels grow on the surface of the retina.

7. BEHAVIOUR — BE

What does your customer do to address the problem and get the job done?
i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace)

This model helps in the early detection of diabetic retinopathy using the fundus images. It consumes less time than the manual examination. Also, accuracy is more compared to other techniques.

Focus on J&P, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS — TR

What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.

The triggers in diabetic retinopathy patients are Spots or dark strings floating in your vision (floaters) Blurred vision, Fluctuating vision, Dark or empty areas in vision, Vision loss

4. EMOTIONS: BEFORE / AFTER

Before: Adverse emotional responses include fear, anxiety. vulnerability, guilt, loss of confidence, anger. After: Early detection and diagnosis gives sense of hope among patients

10. YOUR SOLUTION — SL

If you are working on an existing business, write down your current solution first, fill in the canvas, and check how much it fits reality.
If you are working on a new business proposition, then keep it blank until you fill in the canvas and come up with a solution that fits within customer limitations, solves a problem and matches customer behaviour.

Our solution involves the deep learning model with fundus images that detect the severity of the diabetic retinopathy among diabetic patients and the apt diagnosis done after the early detection.

8. CHANNELS of BEHAVIOUR — CH

8.1 ONLINE
What kind of actions do customers take online? Extract online channels from #7

The diabetic patients have to take the eye examination in the regular interval time. Then only retinopathy can be detected early and proper diagnosis can be done.

Extract online & offline CH of BE

4. REQUIREMENT ANALYSIS

FUNCTIONAL REQUIREMENT

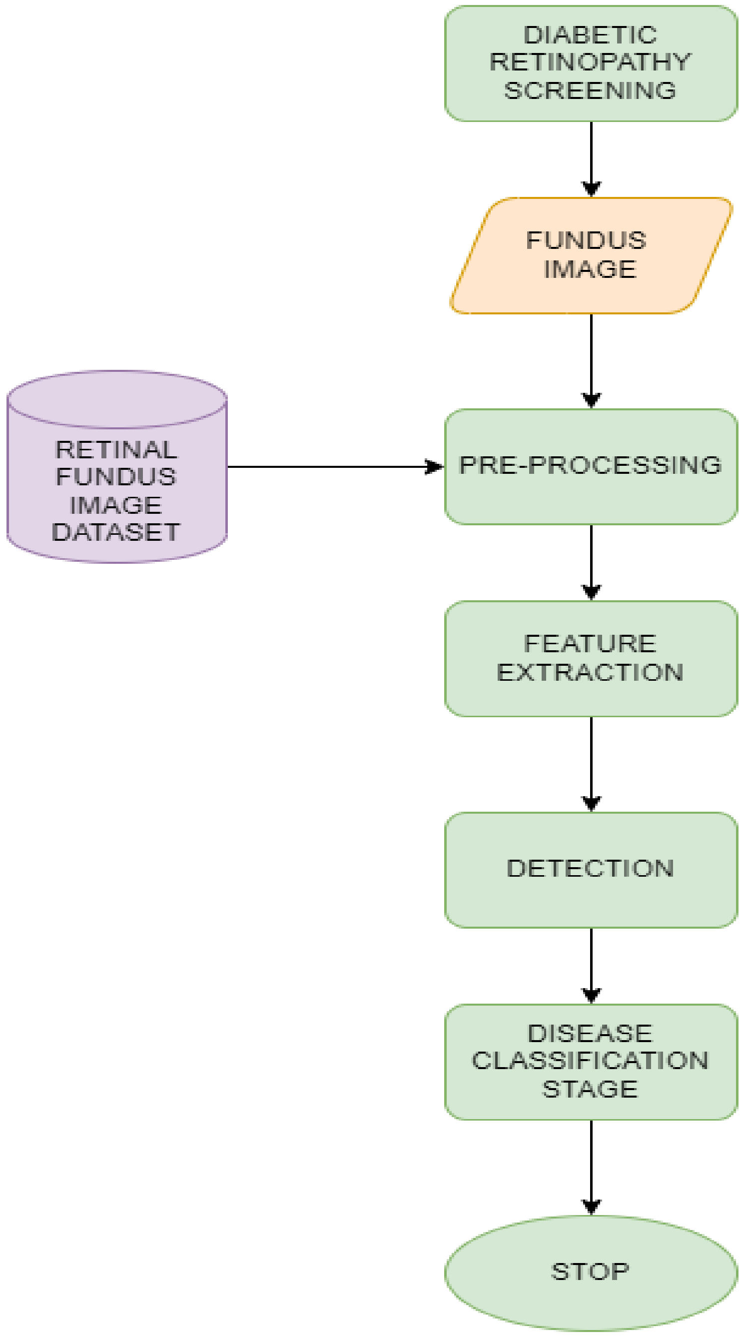
FR No.	Functional Requirement	Sub Requirement
1	Identifying the population eligible for screening	Use registries to ensure that people's details are collected and current, and decide which group needs to be tested based on the best available evidence.
2	Invitation and information	Invite the entire cohort to the screening, and provide information that is appropriate for each group. To facilitate participation with knowledge
3	Testing	Conduct screening tests utilising accepted or advised techniques
4	Referral of screen positives and reporting of screen negative results	Make sure to forward all screening-positive results to the proper agencies, and make sure to inform individuals of any screening negative results so they can continue to participate in the screening programme.
5	Diagnosis	Detect false positives and diagnose real cases
6	Intervention/treatment/follow up	Correctly intervene and treat situations; in some circumstances, surveillance or follow-up may also be necessary.
7	Reporting of outcomes	To identify false negatives and increase the effectiveness and cost-efficiency of the screening programme, collect, evaluate, and report results.

NON-FUNCTIONAL REQUIREMENTS

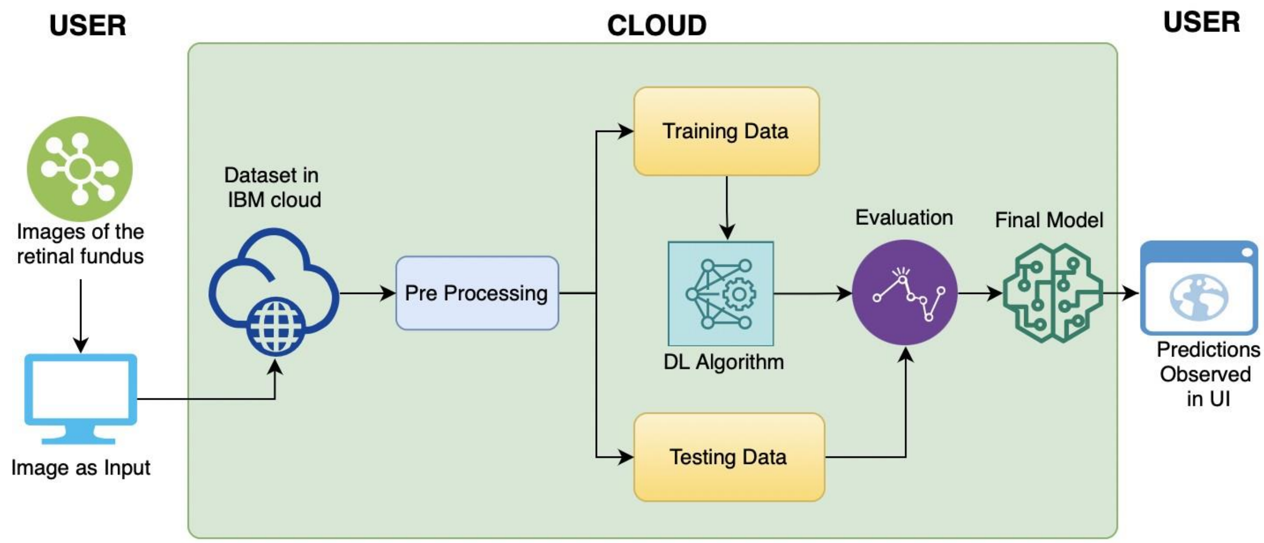
The IBM Watson chatbot is integrated with the proposed system as an additional feature. This is an added advantage for users to communicate easily in the application. This will not affect the functional requirements of the system.

5. PROJECT DESIGN

DATA FLOW DIAGRAMS



SOLUTION & TECHNICAL ARCHITECTURE



Components & Technologies:

S.No	Component	Description	Technology
1.	User Interface	Web UI	HTML, CSS, JavaScript, Python
2.	Application Logic-1	Data Preprocessing	Keras, TensorFlow
3.	Application Logic-2	CNN Model Creation	Keras, TensorFlow, Python
4.	Application Logic-3	Web Application	Flask
5.	Database	Images	Upload Folders
6.	Cloud Database	Database Service on Cloud	IBM Cloudant
7.	File Storage	File storage requirements	IBM Block Storage or Local Drives
8.	External API-1	Keras	IBM preprocessing API
9.	Deep Learning Model	Inception	Object Recognition Model, etc.
10.	Infrastructure (Server / Cloud)	Application Deployment on Cloud Server	Kubernetes

Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Flask	Werkzeug, Jinja2, Sinatra Ruby Framework
2.	Security Implementations	CSRF protection, cookies security flag	Flask-WTF,SESSION_COOKIE_SECURE
3.	Scalable Architecture	Micro Services	Micro web application framework by Flask
4.	Availability	Development server and fast debugger Support for unit testing RESTful request Dispatching Jinja2 template Unicode	Werkzeug,Jinja2.Sinatra Ruby Framework
5.	Performance	ORM-agnostic, web framework, WSGI 1.0 complaint,HTTP request handling functionality high flexibility	SQLAlchemy.extensions, Werkzeug, Jinja2, Sinatra Ruby Framework
6.	Robustness	To increase robustness- training with weight decay, smoothing activation functions, minimizing the Hessian of the network	Python, required Libraries in import activation functions.
7.	Scalability	Clear input pipeline, optimizations	Python, keras.optimizer

USER STORIES

User Type	Functional Requirem-ent	User Story Number	User Story / task	Acceptance criteria	Priority	Release
Common User	Dashboard	USN-1	As a user, I can I must be able to upload image of my eyes	I can upload or take images	High	Sprint -1

		USN-2	As a user, I will receive the diagnosis as to whether I have retinopathy or not	I can receive the diagnosis	High	Sprint -1
		USN-3	As a user, I receive the severity of the retinopathy	I can receive the severity of the retinopathy	Medium	Sprint -2
		USN-4	As a user, can receive the suggested remedy	I can receive the suggested remedy	Medium	Sprint -2

6. PROJECT PLANNING & SCHEDULING

SPRINT PLANNING & ESTIMATION

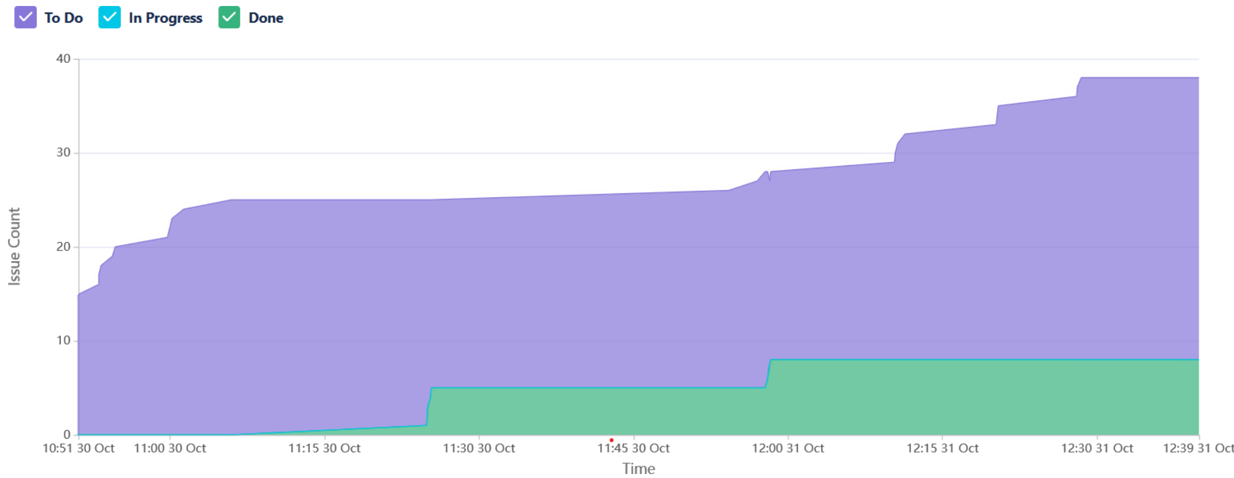
Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-2	Registration	USN-1	As a user, I can register for the application by entering my name, email ID, password	2	High	Thenmozhi,sharmila
Sprint-2		USN-2	As a user, I click on the register button and register for the first time.	1	High	Kiruthika,sasi priya
Sprint-2		USN-3	As a user, If I have an account already or if I have registered successfully, I can click on Login hypertext to redirect to the login page.	2	Low	Mohammed althaf,thenmozhi
Sprint-2	Login	USN-4	As a user, I can enter my email ID and password that I have used for creating account	2	Medium	Sharmila
Sprint-2		USN-5	As a user, I can click the Login button and login to the prediction page.	1	High	Sasi priya,kiruthika
Sprint-3	Validation	USN-7	The entered email and password will be sent as a query variable to check the credential that has been registered already.	2	medium	Mohammed althaf,kiruthika
Sprint-3	Prediction	USN-6	As a user, I have to upload the data by clicking on the button "Choose File".	**2**	low	Thenmozhi, sharmila
Sprint-3		USN-8	As a user, I can upload the file from any general source of storage and upload in the portal.	1	medium	Thenmozhi, sharmila
Sprint-3		USN-9	As a user, I should ensure whether the file is uploaded and click on the submit button.	2	high	Sasi priya,kiruthika
Sprint-1	Uncertainty	USN-10	As a user, I want the prediction to be accurate. I shouldn't be uncertain about the result.	2	High	Thenmozhi,sharmila

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Tangibility	USN-11	As a user, I need the prediction to be perceptible by visualizing.	10	High	Thenmozhi, sharmila
Sprint-4	Integrity	USN-12	As a user, I require the site to remain as it was initially and has not been modified: alteration, deletion or modification.	7	Low	Sasi priya,kiruthika
Sprint-4	Domain dependency	USN-13	As a user, I expect the application to be dependent on operational design	8	Medium	Mohammed althaf,thenmozhi
Sprint-4	Logout	USN-14	As a user, I can log out safely after finding the result.	10	high	sharmila

SPRINT DELIVERY SCHEDULE

Sprint	Total Story Point	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	25 Oct 2022	30 Oct 2022	20	03 Nov 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	16	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	18	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	15	19 Nov 2022

REPORTS FROM JIRA



With proper scheduling and adequate discussions in the 12 meetings set up with the team members, the sprints were effectively completed.

7. CODING & SOLUTIONING

FEATURE 1

The IBM Watson chatbot is integrated with the proposed system as an additional feature as shown in fig 7.1. This is an added advantage for users to communicate easily in the application. This will not affect the functional requirements of the system. IBM Watson Chatbot uses conversational AI to interpret questions, locate or look for better answers, and carry out the user's intended action. It is built on deep learning, machine learning, and natural language processing (NLP) models. Watson as well employs intent categorization and entity identification to understand clients properly in their context and transfer them to a human agent when required. In a recently released machine learning study, Watson chatbot was found to be up to 14.7% higher accuracy than competing alternatives.

```
<script>
    window.watsonAssistantChatOptions = {
      integrationID: "525df91b-26c4-421d-8ba9-9756a0c0bae2", // The ID of this integration.
      region: "au-syd", // The region your integration is hosted in.
      serviceInstanceID: "790053fb-fa61-4744-aff5-8f30a8fa399d", // The ID of your service instance.
      onLoad: function(instance) { instance.render(); }
    };
    setTimeout(function(){
      const t=document.createElement('script');
      t.src="https://web-chat.global.assistant.watson.appdomain.cloud/versions/" + (window.watsonAssistantChatOptions.clientVersion ||
      'latest') + "/WatsonAssistantChatEntry.js";
      document.head.appendChild(t);
    });
  </script>
```

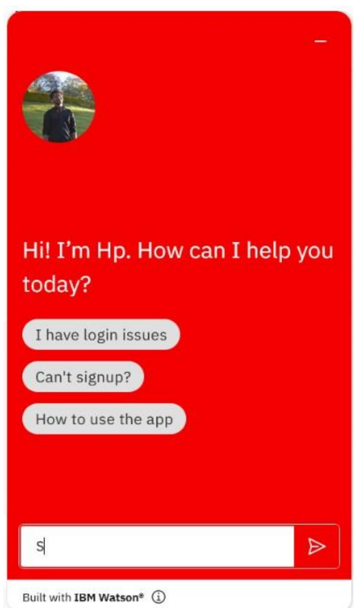


fig 7.1

FEATURE 2

IBM DB2 is utilized in the proposed system. Organizations need a flexible data management foundation, supported by contemporary technology, and dynamic enough to send data wherever it is required to support quick decisions. Fast data retrieval, queries, and disc space compression have the potential to increase transaction response time by 30%. IBM database2 is advantageous for handling GDPR compliance, use of advanced authorization, encryption in transit and at rest and extensive security controls. IBM DB2 supports in maintaining application operations around-the-clock and to use IBM pureScale clustering, auto resynchronization and recovery.

```
conn = ibm_db.connect("DATABASE=bludb;HOSTNAME=98538591-7217-4024-b027-8baa776ffad1.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud;PORT=30875;
SECURITY=SSL;SSLServerCertificate=DigiCertGlobalRootCA.crt;UID=tmd49992;PWD=f8N7KQcnld7HlGKl",'','')  # type: ignore
print(conn)
print("connection successful...")
```

fig 7.2

DATABASE SCHEMA

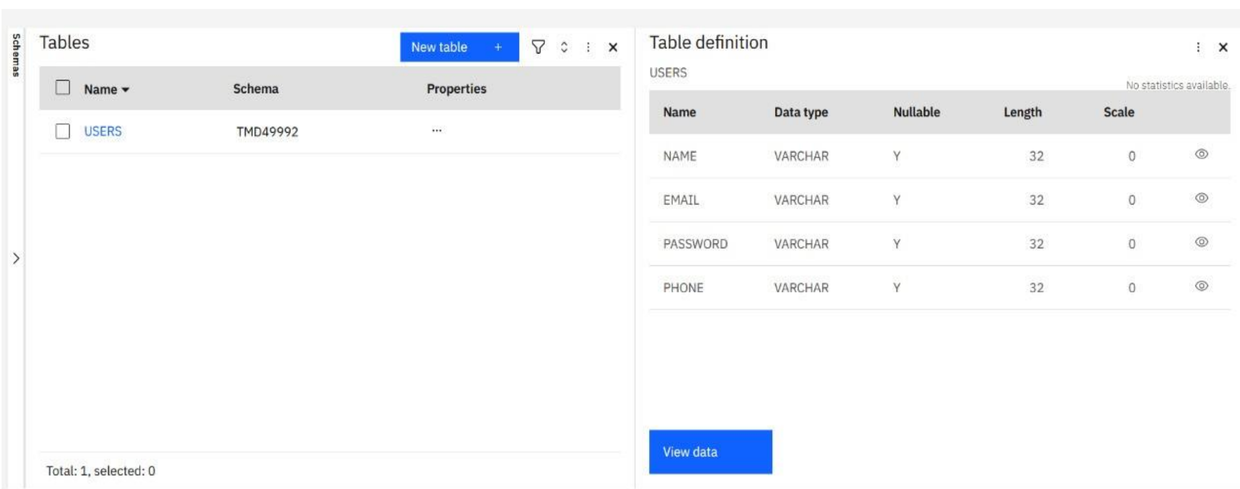


fig 7.3

fig 7.3 shows the table with attributes name,datatype,nullable,length,scale are being used for all the users details and there are no statistics available.

```python
# prediction page
@app.route('/result', methods=['GET','POST'])
def res():
    if request.method=='POST':
        f = request.files['image']
        basepath = os.path.dirname(__file__) # getting the current directory
        #print("current path", basepath)
        file_path = os.path.join(basepath, 'uploads', f.filename) # joining the current directory with the uploads folder
        #print("upload path", file_path)
        f.save(file_path) # saving the file to the uploads folder

        # predicting the image
        img = image.load_img(file_path, target_size=(299, 299))
        x = image.img_to_array(img)
        x = np.expand_dims(x, axis=0)
        #print(x)
        img_data = preprocess_input(x)
        prediction = np.argmax(model.predict(img_data), axis=1)

        #prediction = model.predict(x)  # instead of predic_classes, use predict
        #print(prediction)
        index = ['No Diabetic Retinopathy', 'Mild DR', 'Moderate DR', 'Severe DR', 'Proliferative DR']
        #result = str(index[output[0]])
        result = str(index[prediction[0]])
        print(result)
        return render_template('stats.html', prediction = result)
```

fig 7.4

fig 7.4 shows the prediction page gives the result as the retinopathy is Mild or Moderate or Severe or Proliferate or the person with no retinopathy.

```python
# Upload model
model = load_model(r'Updated-Xception-diabetic-retinopathy.h5')


# Define a flask app
app = Flask(__name__)

# Authenticate using an IAM API key.
client = Cloudant.iam('e0b548a4-365a-4c1b-83c5-504494b2a97c-bluemix', '6TODExgQLwDgTGDZCUY0TKUyMdQqI3gGVsn1WtCnUQsa', connect=True)
```

fig 7.5

fig 7.5 shows the previously trained model is being saved as .h5 and it is being uploaded .

```python
import configparser
import sendgrid
from sendgrid.helpers.mail import Mail
config = configparser.ConfigParser()
import base64

config.read('mail.env')
APIKEY = config.get('API', 'APIKEY')
api = sendgrid.SendGridAPIClient(APIKEY)
FROM_EMAIL = config.get('API','FROM_EMAIL')
def sendemail(user,content):
    TO_EMAIL = user
    mail = Mail(from_email=FROM_EMAIL,to_emails=TO_EMAIL,subject='Hey there! We heard from you!',html_content=f'<strong>{content}</strong>')
    response = api.send(mail)
    print(response.status_code)
    print(response.headers)
```

fig 7.6

fig 7.6 shows the code for User interface having the Mail feature .

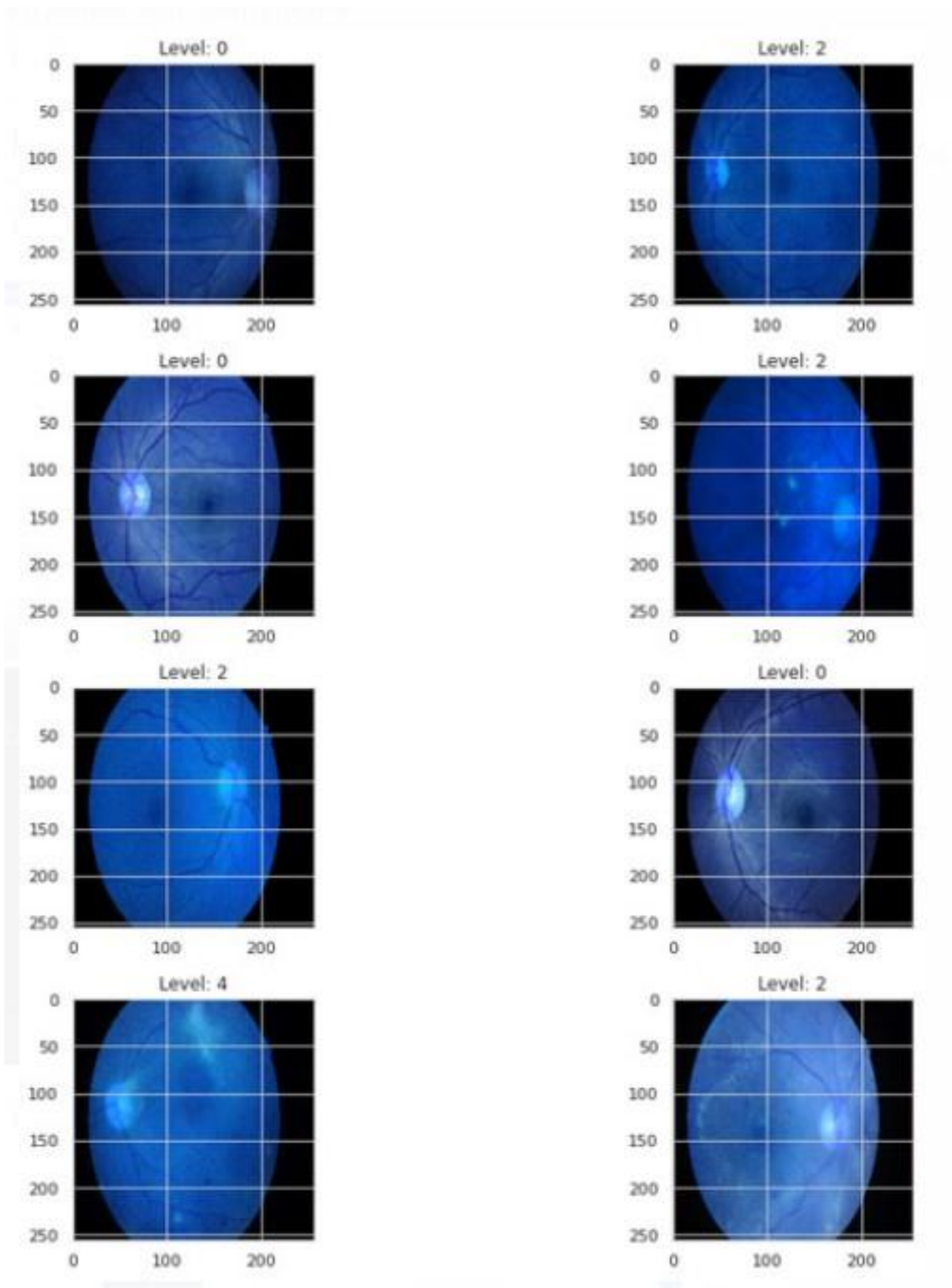


fig 7.7 The Preprocessed input is shown.

8. TESTING

TEST CASES

The outcomes were relevant to the methods put in place using the suggested framework. In CNN, recognition accuracy as the function computes was reduced, whereas it lowered whenever the filtering size increases. These are the general findings and comparison. The following equations are utilized to evaluate sensitivity, specificity and accuracy predicated on the confusion matrix.

- **ACCURACY METRIC**: One metric for measuring classification model performance is accuracy. Informally, accuracy is the percentage of predictions that our model correctly predicted.

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+FN+TN}$$

- **SENSITIVITY**: The metric used to assess a model's capacity to forecast the true positives of each accessible category is known as the true positive prediction metric in machine learning. This phrase has a literary equivalent known as a real positive rate.

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$

- **SPECIFICITY**: These are generally defined as the algorithm's or model's power to anticipate a valid negative for each accessible category.

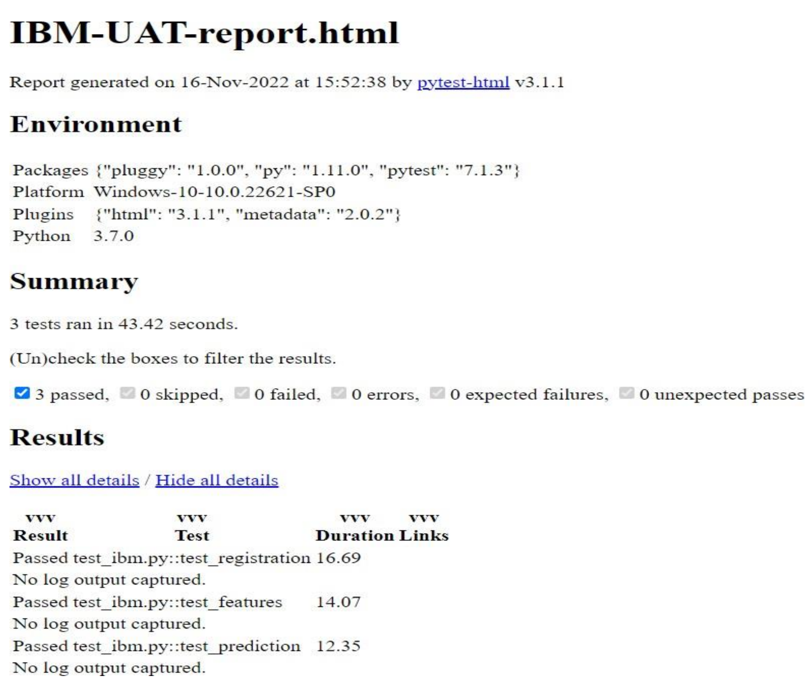
$$\text{Specificity}=\frac{TN}{TN+FP}$$

- **VALIDATION ACCURACY:** This proposed model's result is that the elimination of multiple redundant parameters and layers leads to a reduction in classification time. By evaluating the accuracy rate for validation, the capacity of determining that the suggested model had a 96% accuracy rate for validation.

NOTE: TP-True positive, TN- True Negative , FP- False positive, FN-False negative.

USER ACCEPTANCE TESTING

Application testing, often known as user acceptance testing (UAT), represents the final phase of almost any application development or scope change lifecycle before appearing online. Validating whether the software performs as expected in exact conditions represents the final milestone in any development cycle. If the application has not been well accepted by its target users, it may still not fulfil the criteria even after undergoing additional testing phases and to be functioning properly. This could occur if the developers' understanding of the software's requirements was lacking, if the project's scope altered as a result of development changes, or if the system just wasn't ready to be tested in a dynamic, real-world setting. Overall, UAT prevents the delivery of flawed, useless, or incomplete software products.



IBM-UAT-report.html

Report generated on 16-Nov-2022 at 15:52:38 by pytest-html v3.1.1

Environment

Packages	{"pluggy": "1.0.0", "py": "1.11.0", "pytest": "7.1.3"}
Platform	Windows-10-10.0.22621-SP0
Plugins	{"html": "3.1.1", "metadata": "2.0.2"}
Python	3.7.0

Summary

3 tests ran in 43.42 seconds.

(Un)check the boxes to filter the results.

3 passed, 0 skipped, 0 failed, 0 errors, 0 expected failures, 0 unexpected passes

Results

Show all details / Hide all details

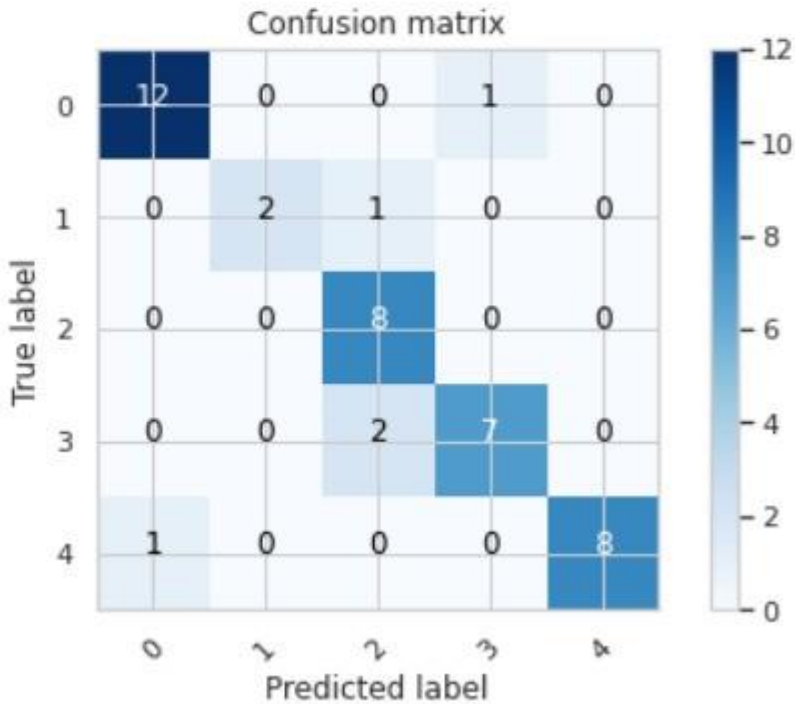
Result	Test	Duration	Links
Passed	test_ibm.py::test_registration	16.69	
No log output captured.			
Passed	test_ibm.py::test_features	14.07	
No log output captured.			
Passed	test_ibm.py::test_prediction	12.35	
No log output captured.			

Fig 8.1: User Acceptance Testing Report for Deep Learning Fundus Image Analysis For Early Detection Of Diabetic Retinopathy.

9. RESULTS

PERFORMANCE METRICS

Confusion Matrix



The confusion matrix represents the result of the combination of the residual neural network (ResNet) and VGG model that is used to predict the diabetic retinopathy diseases. The model is applied on a multi-class dataset that consists of five categories. The 5x5 matrix represents the TF, TT, FT, FF prediction rate of the model.

True positive (TP), observation is predicted positive and is actually positive. False positive (FP), observation is predicted positive and is actually negative. True negative (TN), observation is predicted negative and is actually negative. False negative (FN), observation is predicted negative and is actually positive.

Accuracy

Accuracy gives the proportion of the total number of predictions that were correct. Accuracy=TP+TN/TP+FP+TN+FN

```
Epoch 12/15
60/60 [==============================] - 6s 102ms/step - loss: 0.0060 - accuracy: 0.9932 - val_loss: 0.2013 - val_accuracy: 0.9467
Epoch 13/15
60/60 [==============================] - 6s 103ms/step - loss: 0.0061 - accuracy: 0.9966 - val_loss: 0.2173 - val_accuracy: 0.9200
Epoch 14/15
60/60 [==============================] - 6s 104ms/step - loss: 0.0254 - accuracy: 0.9932 - val_loss: 0.1428 - val_accuracy: 0.9600
Epoch 15/15
60/60 [==============================] - 6s 100ms/step - loss: 0.0062 - accuracy: 0.9966 - val_loss: 0.1529 - val_accuracy: 0.9467
<keras.callbacks.History at 0x7f8ced38e6d0>
```

The figure represents the accuracy value of the model classification. The model was trained by fifteen epochs.

Precision

Precision or the positive predictive value, is the fraction of positive values out of the total predicted positive instances. In other words, precision is the proportion of positive values that were correctly identified.

Precision=TP/TP+FP

Sensitivity

Sensitivity, recall, or the TP rate (TPR) is the fraction of positive values out of the total actual positive instances (i.e., the proportion of actual positive cases that are correctly identified)

Sensitivity=TP/TP+FN

Specificity

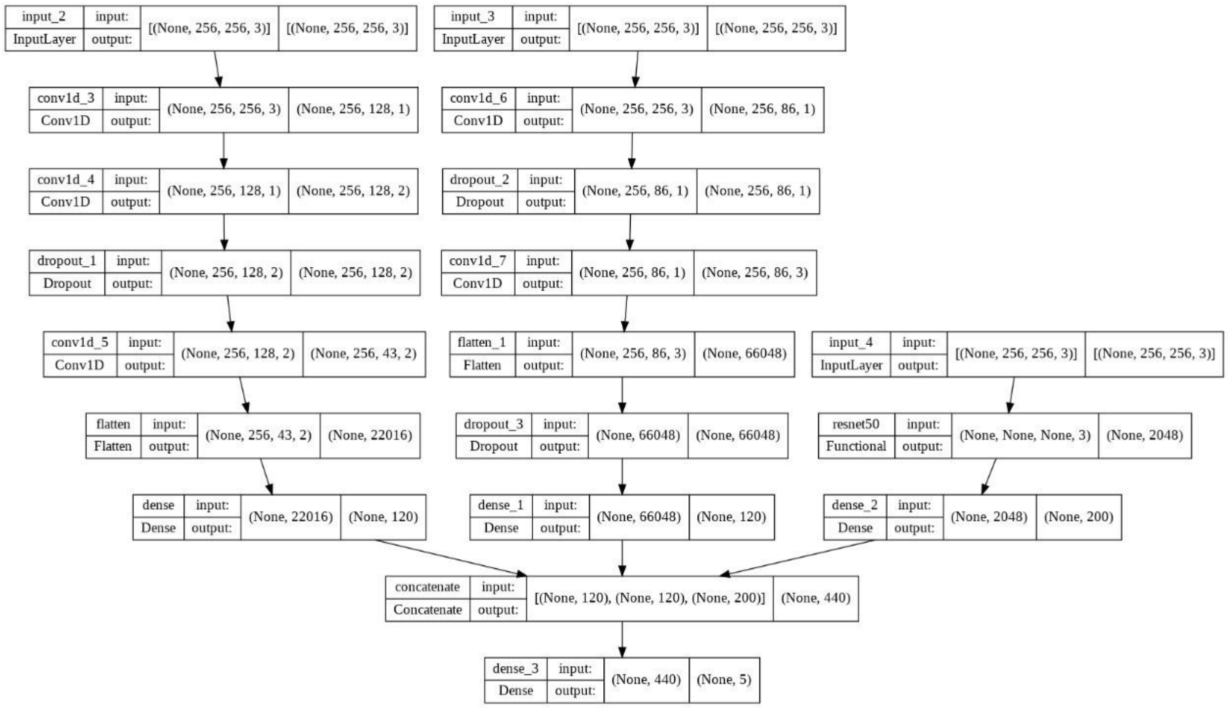
Specificity gives the fraction of negative values out of the total actual negative instances. In other words, it is the proportion of actual negative cases that are correctly identified. The FP rate is given by (1 – specificity)

Specificity=TN/TN+FP

F1 score

The $F1$ score, F score, or F measure is the harmonic mean of precision and sensitivity it gives importance to both factors

Hybrid Model:



The mode takes half a set of input instances to ResNet and the other half data to the VGG algorithm. The input is convoluted and flattened to produce certain output. These outputs from ResNet and VGG are combined to give a result of the whole dense layered hybrid model.

10. ADVANTAGE & DISADVANTAGES

Methods based on Artificial Intelligence and in particular Deep Learning, carry the potential for enhancing and advancing healthcare. To ease the implementation of AI in healthcare settings, a number of significant obstacles must be managed to overcome. A number of other factors are identified as crucial steps for the approval of AI models through regulatory processes, in addition to the conventional methods that are used to evaluate the model's performance, such as accuracy measures. Although the transition from conventional to deep learning machine learning methodologies has increased the performance of these analyses, it has also been accompanied by a lack of clarity and comprehensibility. However, a key factor influencing their acceptability and incorporation in clinical practice seems to be how interpretable such models appear. The model's decision-making process must be understood by the professional user and should preferably explain how it arrived at its predictions.

11. CONCLUSION

A major consequence of diabetes mellitus, diabetic retinopathy causes gradual retinal degeneration and can even result in blindness. To stop it from getting worse and harming the retina, it is crucial to find and treat it early. Since numerous DL systems have evolved and been integrated into medical care, there has been an increased interest in using them to diagnose diabetic retinopathy. This will help physicians treat patients more effectively and efficiently. This report outlines the advancements in investigations on using deep learning to diagnose diabetic retinopathy.

In the proposed model, Expectation-Maximization (EM) algorithm was tried to classify the categories. But the model produced a very low rate of accuracy, 75%. The flaw led to the alternative solution of using a combination of ResNet and VGG as a hybrid model to classify the highness of diabetic retinopathy. Finally this hybrid model resulted in 99 % accuracy.

12. FUTURE SCOPE

Furthermore, incorporating more patient metadata that may enhance their chance of acquiring retinopathy, such as genetic variables, the length of their diabetes, the haemoglobin A1C number, and other clinical information could be beneficial to integrate particular data about explicit disease aspects in the classification models. This could advance the AI model by producing illuminating insights into the underlying Diabetic Retinopathy risk variables and possibly improve diagnostic performance.

13. APPENDIX

GitHub & Project Demo Link

Github link:

The source code of the complete project is provided in the following github repository.

Final Deliverables/Flask Application

Hybrid model saved file:

https://drive.google.com/file/d/1aE9q1llWL9clGioauLsGMn8GK7NiVfvy/view?usp=sharing

Project Demo Link:

https://drive.google.com/file/d/1HuvaCz1IMW-PmlKcMld3PiF6CVVNnHhn/view?usp=sharing

14. BIBLIOGRAPHY

[1] X. Li, T. Pang, B. Xiong, W. Liu, P. Liang, and T. Wang, "Convolutional neural networks based transfer learning for diabetic retinopathy fundus image classification," Proceedings - 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI 2017, vol. 2018-January, pp. 1–11, Feb. 2018, doi: 10.1109/CISP-BMEI.2017.8301998.

[2] S. Mohammadian, A. Karsaz, and Y. M. Roshan, "Comparative Study of Fine-Tuning of Pre-Trained Convolutional Neural Networks for Diabetic Retinopathy Screening," 2017 24th Iranian Conference on Biomedical Engineering and 2017 2nd International Iranian Conference on Biomedical Engineering, ICBME 2017, Aug. 2018, doi: 10.1109/ICBME.2017.8430269.

[3] P. Khojasteh et al., "Exudate detection in fundus images using deeply-learnable features," Computers in Biology and Medicine, vol. 104, pp. 62–69, Jan. 2019, doi: 10.1016/J.COMPBIOMED.2018.10.031.

[4] M. R. Islam et al., "Applying supervised contrastive learning for the detection of diabetic retinopathy and its severity levels from fundus images," Computers in Biology and Medicine, vol. 146, p. 105602, Jul. 2022, doi: 10.1016/J.COMPBIOMED.2022.105602.

[5] M. Mateen, J. Wen, N. Nasrullah, S. Sun, and S. Hayat, "Exudate Detection for Diabetic Retinopathy Using Pretrained Convolutional Neural Networks," Complexity, vol. 2020, 2020, doi: 10.1155/2020/5801870.

[6] L. Math and R. Fatima, "Adaptive machine learning classification for diabetic retinopathy," Multimedia Tools and Applications 2020 80:4, vol. 80, no. 4, pp. 5173–5186, Oct. 2020, doi: 10.1007/S11042-020-09793-7.

[7] V. Deepa, C. Sathish Kumar, and T. Cherian, "Automated grading of diabetic retinopathy using CNN with hierarchical clustering of image patches by siamese network," Physical and Engineering Sciences in Medicine 2022 45:2, vol. 45, no. 2, pp. 623–635, May 2022, doi: 10.1007/S13246-022-01129-Z.

[8] M. A. BERBAR, "Diabetic Retinopathy Detection and Grading using Deep learning," Menoufia Journal of Electronic Engineering Research, vol. 0, no. 0, pp. 11–20, Jun. 2022, doi: 10.21608/MJEER.2022.138003.1057.

[9] A. Karsaz, “A modified convolutional neural network architecture for diabetic retinopathy screening using SVDD,” Applied Soft Computing, vol. 125, p. 109102, Aug. 2022, doi: 10.1016/J.ASOC.2022.109102.

[10] M. A. Berbar, “Features extraction using encoded local binary pattern for detection and grading diabetic retinopathy,” Health Information Science and Systems 2022 10:1, vol. 10, no. 1, pp. 1–13, Jun. 2022, doi: 10.1007/S13755-022-00181-Z.