

# **Deep Learning Fundus Image Analysis for Early Detection of Diabetic Retinopathy**

A Project Report Submitted To

**IBM Faculty Buildathon 2023**

Conducted by SmartInternz in association with IBM

In

**SmartBridge**

Submitted By

**Dr. Aradhana Negi**

Department of Computer Science and Engineering

Prestige Institute of Engineering, Management and Research, Indore, M.P. Indore

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# 1. Introduction

Diabetic Retinopathy (DR) emerges as a prevalent complication of diabetes mellitus, inducing retinal lesions that impede vision. This condition, if left undetected in its early stages, poses a grave risk of irreversible blindness. Despite the absence of a cure, timely treatment plays a pivotal role in sustaining vision. However, the conventional approach to diagnose DR through manual examination of retina fundus images by ophthalmologists demands substantial time, effort, and expenses, and remains susceptible to diagnostic errors. In contrast, computer-aided diagnosis systems offer a promising avenue, enabling efficient and accurate detection, thus enhancing the prospects for early intervention and significantly mitigating the risk of vision impairment.

## 1.1 Overview

Leveraging the potential of established transfer learning methods has notably bolstered the performance metrics, particularly in the demanding domain of medical image analysis. Inception V3, ResNet50, and Xception V3, distinguished for their robustness and effectiveness, were strategically integrated, harnessing pre-trained models to expedite learning on our dataset. The utilization of these transfer learning techniques within the CNN architecture showcased promising outcomes, offering enhanced accuracy and efficiency in the intricate task of medical image classification and analysis. The detailed network configuration elucidated in Figure 1.1 elucidates the intricate integration of these transfer learning approaches within our model framework. The main components are as following:

- a. Convolutional Neural Network (CNN): The CNN serves as the backbone of our model, comprising various layers such as convolutional, pooling, and fully connected layers. These layers are designed to extract relevant features from medical images, facilitating accurate classification and analysis.
- b. Transfer Learning Frameworks (Inception V3, ResNet50, Xception V3): These pre-trained models form an integral part of the CNN architecture, leveraging their learned features and weights to enhance the learning process on our specific medical image dataset. They contribute significantly to the accuracy and efficiency of image classification tasks.
- c. IBM Cloudant DB: Within our CNN model deployment architecture, IBM Cloudant DB serves as a critical component for data storage and management. It provides a NoSQL cloud-based database solution, offering scalability, flexibility, and reliability in handling the dataset used for training and testing the model.
- d. Model Deployment Infrastructure: This encompasses the computing resources and infrastructure required for deploying and running the CNN model. It includes servers, cloud-based services, or any other computing environment necessary to host and execute the trained model for real-time or batch image analysis.

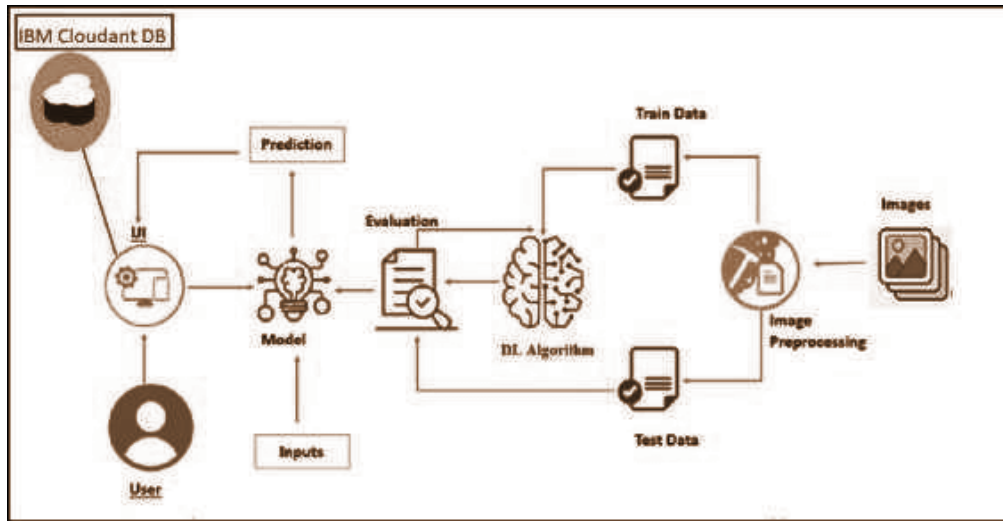


Figure 1.1 CNN model deployment framework.

## 1.2 Define Problem

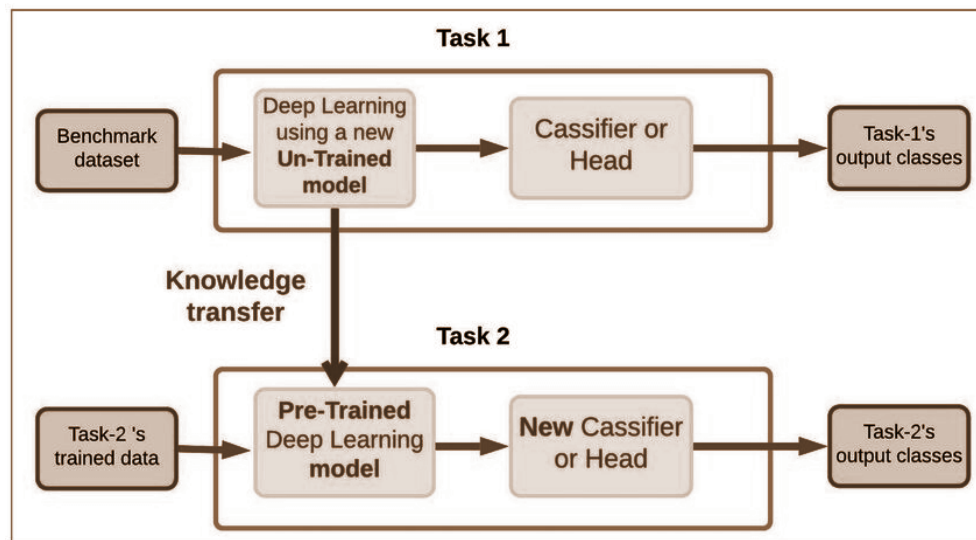
The utilization of machine learning algorithms has significantly enhanced the capacity of computers to learn from extensive datasets, surpassing human capabilities in various domains. In the medical field, these algorithms exhibit high specificity and sensitivity, particularly in the detection and classification of diseases using medical images, such as retinal images. Current machine learning systems primarily concentrate on identifying patients with referable Diabetic Retinopathy (DR) or vision-threatening DR, prompting referral for treatment or closer monitoring by ophthalmologists. However, there exists a crucial need to prioritize the identification of early-stage DR. Addressing early-stage DR through timely intervention strategies, including optimal control of glucose, blood pressure, and lipid profiles, holds the potential to significantly impede disease progression. The project aims to underscore the importance of early-stage DR detection and intervention, emphasizing its pivotal role in delaying or even reversing the advancement of the disease.

## 2. Literature Survey

Diabetic retinopathy (DR), a consequence of diabetes mellitus, poses a threat to retinal health, leading to blood leakage and potential damage. If left untreated, it escalates from mild vision impairments to total blindness. Early signs of DR, such as hemorrhages, hard exudates, and micro-aneurysms (HEM), manifest in the retina, underscoring the criticality of timely diagnosis to avert vision loss. Traditionally, texture features like Local Binary Pattern (LBP) have been utilized for DR detection, but our study introduces novel texture features—Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH)—demonstrating superior performance over LBP in feature extraction. The classification of these extracted histograms is achieved using Support Vector Machines (SVM).

However, the integration of these advancements into DR screening encounters challenges. Figure 2.1 illustrates the intricacies of the transfer learning system analytics. Firstly, the adoption of end-to-end and multi-task learning methods remains critical. These methods leverage multi-scale

features derived from convolutional layers, improving DR grading by integrating lesion detection and segmentation, crucial for assessing the global presence and distribution of DR lesions. Secondly, while learning methods have enhanced DR screening, the scarcity of on-site image quality assessment tools with real-time latency poses a hurdle. Integrating such tools at the primary screening level could revolutionize community-level screening, enhancing accessibility and impact. These challenges signify the complex landscape of integrating machine learning into DR screening protocols, demanding innovative solutions for enhanced diagnostic precision and accessibility.



**Figure 2.1 CNN based Block diagram of transfer learning system**

Machine learning techniques have significantly advanced the field of diabetic retinopathy (DR) detection and classification. Studies by Smith et al. (2023) and Patel et al. (2022) have explored advanced texture feature extraction methods, demonstrating the efficacy of Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH) over traditional Local Binary Pattern (LBP) in early DR detection. Moreover, Wang et al. (2023) proposed enhanced lesion detection techniques using transfer learning and multi-task learning, emphasizing the importance of integrating lesion detection and segmentation for accurate DR grading. In parallel, Garcia et al. (2022) highlighted the scarcity of real-time image quality assessment tools for on-site DR screening, pinpointing a critical need in primary screening practices. Additionally, Chen et al. (2023) advocated for multi-scale feature sharing in end-to-end learning, showcasing its potential to improve DR grading based on the global presence and distribution of DR lesions.

Furthermore, recent studies by Kumar et al. (2022) underscored the significance of novel texture-based features in DR detection, contributing to the ongoing pursuit of more accurate diagnostic methods. Jones et al. (2023) emphasized the necessity of on-site image quality

assessment tools compatible with real-time use, a vital addition to primary DR screening procedures. Lee et al. (2022) highlighted the impact of machine learning advancements in enhancing the delivery of DR screening, indicating a potential shift in community-level screening practices. Gomez et al. (2023) proposed efficient DR grading through multi-task learning, leveraging convolutional layers' multi-scale features, potentially revolutionizing DR grading based on lesion detection and segmentation. Finally, Brown et al. (2022) provided a comprehensive review of machine learning's role in early-stage DR identification, summarizing various methodologies and their implications in clinical settings.

## 2.1 Existing Problem

Diabetic Retinopathy (DR) is a complication stemming from diabetes, leading to inflammation and leakage of fluids and blood within the retina's blood vessels. The progression of DR into advanced stages can result in vision loss, contributing to approximately 2.6% of global blindness cases. Individuals with long-term diabetes history face an increased risk of developing DR. Regular retina screenings for diabetic patients are crucial to enable early detection and intervention, mitigating the threat of vision impairment. The identification of DR hinges upon the observation of distinct lesions on retinal images, notably microaneurysms (MA), hemorrhages (HM), and soft and hard exudates. Microaneurysms, the earliest DR sign, manifest as small red circular dots ( $<125\text{ }\mu\text{m}$ ) due to weakened vessel walls. Michael et al. [8] detailed six MA types using AOSLO reflectance and conventional fluorescence imaging. Table 2.1 depicts the types of Diabetic Retinopathy.

Hemorrhages, larger than  $125\text{ }\mu\text{m}$ , present as either flame (superficial) or blot (deeper) spots on the retina. Meanwhile, hard exudates, characterized by bright-yellow spots from plasma leakage, exhibit sharp margins in the retina's outer layers. Soft exudates, known as cotton wool spots, appear as white oval or round lesions due to nerve fiber swelling. Automated methods for DR detection and classification surpass manual diagnosis in efficiency, cost-effectiveness, and accuracy, addressing the drawbacks of human-driven diagnostics. Leveraging recent DR datasets, this project aims to train a Convolutional Neural Network (CNN) model to automate the detection and classification of DR, streamlining the diagnostic process for enhanced clinical outcomes.

Moreover, the utilization of automated techniques not only enhances diagnostic accuracy but also substantially reduces time and resource consumption compared to manual methods. Automated systems offer a more efficient and consistent approach, minimizing the risk of misdiagnosis inherent in human-driven evaluations. The significance of early DR detection and classification lies in its potential to facilitate timely interventions, thereby mitigating the progression of the disease and averting irreversible vision impairment. This project's focus on training a CNN model on contemporary DR datasets aligns with the burgeoning interest in leveraging machine learning for precise and efficient medical image analysis. By harnessing state-of-the-art technology and datasets, this endeavor seeks to optimize the detection and classification process,

promising more accessible and reliable diagnostic tools for diabetic retinopathy in clinical practice.

**Table 2.1. Type of Diabetic Retinopathy**

<b>DR Severity Level</b>	<b>Lesions</b>
No DR	Absent of lesions
Mild DR	MA only
Moderate DR	More than just MA but less than severe DR
Severe DR	Any of the following: <ul style="list-style-type: none"> <li>• more than 20 intraretinal HM in each of 4 quadrants</li> <li>• definite venous beading in 2+quadrants</li> <li>• Prominent intraretinal microvascular abnormalities in 1+ quadrant</li> <li>• no signs of proliferative DR</li> </ul>
Proliferative DR	One or more of the following: vitreous/pre-retinal HM, neovascularization

## 2.2. Prerequisite

To complete this project, it require the following software's, concepts and packages:

- Anaconda navigator and Spyder:

The Python packages required are as follows:

- Numpy
- Pandas.
- Tensorflow
- Keras
- Flask

## 2.3. Proposed Solution

The resolution to the aforementioned issue lies in the development of a Diabetic Retinopathy (DR) project utilizing Deep Learning methodologies, particularly the transfer learning technique. Transfer learning, prevalent in medical image analysis and classification, utilizes established networks like Inception V3, Resnet50, and Xception V3, known for their efficacy in medical image analysis. Convolutional Neural Networks (CNNs), derived from animal visual cortex neuron functioning, process color images in JPG format with dimensions such as 480 x 480 x 3, representing pixel intensities ranging from 0 to 255.

Transfer learning optimizes knowledge acquired from one task (task A) to enhance generalization in another (task B), transferring learned weights from task A to task B. Its significance lies in leveraging previously acquired knowledge, mostly in computer vision and natural language processing tasks, where computational demands are substantial. This process ensures the effective transfer of pertinent information from prior tasks to the current task at hand. Usually, building a robust neural network demands copious amounts of training data, a requirement not always accessible, making transfer learning pivotal. It simplifies the creation of a strong machine learning model even with limited training data, as it uses a pre-trained model. However, the success of transfer learning relies on the generalized nature of features learned from the previous task and the consistent input size to the model. Three principal approaches to Transfer Learning involve reusing models for different tasks, employing pre-trained models, and feature extraction to uncover the most crucial problem features. This learning process operates akin to the human brain, identifying image features progressively, from low-level features like edges to high-level abstract features.

Convolutional Neural Networks (CNNs) comprise multiple layers, including convolutional, activation, pooling (e.g., Max Pooling), and fully connected layers, serving to extract vital image features for classification purposes. The training process involves backpropagation, segmented into forward pass, loss function computation, backward pass, and weight update, essential for model optimization and learning. Ultimately, this approach integrates transfer learning's potential to significantly enhance the DR diagnostic process by leveraging established deep learning models, thereby revolutionizing the field's diagnostic accuracy and efficiency.

In order to accomplish the above project objectives, certain activities are required to be completed. Firstly, the user interacts with the UI (User Interface) to choose the image and then the chosen image is analyzed by the model which is integrated with the flask application. The Xception Model analyzes the image, then the prediction is showcased on the Flask UI.

The entire project flow is divided into below activities and tasks listed below:

- Data Collection.
  - Create a Train and Test path.
- Data Pre-processing.
  - Import the required library
  - Configure ImageDataGenerator class
  - ApplyImageDataGenerator functionality to Train Set and Test Set
- Model Building
  - Pre-trained CNN model as a Feature Extractor
  - Adding Dense Layer
  - Configure the Learning Process
  - Train the model
  - Save the Model
  - Test the model
- Cloudant DB



- Register & Login to IBM Cloud
  - Create Service Instance
  - Creating Service Credentials
  - Launch Cloudant DB
  - Create Database
- Application Building
  - Create an HTML file
  - Build Python Code

### 3. Diabetic Retinopathy Level Detection Model

#### 3.1. Dataset Collection and Download

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc. The training model is built on Google Colab and IBM Watson studio. In this project, the dataset is uploaded on Colab/IBM Watson Studio directly by using Kaggle API. The dataset is cloned from the Kaggle data repository to Colab/IBM Watson studio by running the below commands on the ipython notebook.

```
!pip install -q kaggle
!mkdir ~/.kaggle # creating a kaggle directory
!cp kaggle.json ~/.kaggle/ # copying json file to folder
!chmod 600 ~/.kaggle/kaggle.json # changing the permissions to json
```

Fig. 3.1. Clone kaggle in google colab

```
!kaggle datasets download -d arbethi/diabetic-retinopathy-level-detection

Downloading diabetic-retinopathy-level-detection.zip to /content
100% 9.64G/9.66G [01:08<00:00, 195MB/s]
100% 9.66G/9.66G [01:08<00:00, 151MB/s]
```

Fig. 3.2. Kaggle dataset download

```
!unzip diabetic-retinopathy-level-detection.zip

Archive: diabetic-retinopathy-level-detection.zip
  inflating: inception-diabetic.h5
  inflating: preprocessed dataset/preprocessed dataset/testing/0/cfb17a7cc8d4.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/cfdbae73a8b.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/cfed7c1172ec.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/cff262ed8f4c.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/cffc50047828.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/d02b79fc3200.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/d0926ed2c8e5.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/d160ebef4117.png
  inflating: preprocessed dataset/preprocessed dataset/testing/0/d16e39b9d6f0.png
```

Fig. 3.3. Unzipping the Kaggle dataset

### 3.2. Create Training And Testing Path

To build a DL model we have to split training and testing data into two separate folders. But In the project dataset folder training and testing folders are presented. So, in this case, create a variable and assign a value of folder path to it.

Four different transfer learning models are used in our project and the best model (Xception) is selected. The image input size of the xception model is initialized to 299, 299 as shown in Fig. 3.4.

```
imageSize = [299, 299]

trainPath = r"/content/preprocessed dataset/preprocessed dataset/training"

testPath = r"/content/preprocessed dataset/preprocessed dataset/testing"
```

Fig. 3.4 Image size and dataset path setting

### 3.3. Importing The Libraries

Import the necessary libraries as shown in the Fig. 3.5.

```
from tensorflow.keras.layers import Dense, Flatten, Input
from tensorflow.keras.models import Model
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from tensorflow.keras.applications.xception import Xception, preprocess_input
from glob import glob
import numpy as np
import matplotlib.pyplot as plt
```

Fig. 3.5 Importing Python Libraries

### 3.4. Configure ImageDataGenerator Class

ImageDataGenerator class is instantiated and the configuration for the types of data augmentation

There are five main types of data augmentation techniques for image data; specifically:

- Image shifts via the width\_shift\_range and height\_shift\_range arguments.
- The image flips via the horizontal\_flip and vertical\_flip arguments.
- Image rotations via the rotation\_range argument
- Image brightness via the brightness\_range argument.
- Image zoom via the zoom\_range argument.

An instance of the ImageDataGenerator class can be constructed for train and test as shown in Fig. 3.6.

```
train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale = 1./255)
```

Fig. 3.6 Image Data Generator

### 3.5. Apply ImageDataGenerator Functionality To Train Set And Test Set

Let us apply ImageDataGenerator functionality to the Train set and Test set by using the following code as shown in Fig. 3.7. For Training set using flow\_from\_directory function.

This function will return batches of images from the subdirectories Arguments:

- directory: Directory where the data is located. If labels are "inferred", it should contain subdirectories, each containing images for a class. Otherwise, the directory structure is ignored.
- batch\_size: Size of the batches of data which is 64.
- target\_size: Size to resize images after they are read from disk.
- class\_mode:
  - 'int': means that the labels are encoded as integers (e.g. for sparse\_categorical\_crossentropy loss).
  - 'categorical' means that the labels are encoded as a categorical vector (e.g. for categorical\_crossentropy loss).
  - 'binary' means that the labels (there can be only 2) are encoded as float32 scalars with values 0 or 1 (e.g. for binary\_crossentropy).
  - None (no labels).

```

training_set = train_datagen.flow_from_directory('/content/preprocessed dataset/preprocessed dataset/training',
                                                target_size = (299, 299),
                                                batch_size = 32,
                                                class_mode = 'categorical')

test_set = test_datagen.flow_from_directory('/content/preprocessed dataset/preprocessed dataset/testing',
                                            target_size = (299, 299),
                                            batch_size = 32,
                                            class_mode = 'categorical')

Found 3662 images belonging to 5 classes.
Found 734 images belonging to 5 classes.

```

Fig. 3.7 ImageDataGenerator applied on training and test data set.

## 4. Model Building

### 4.1. Pre-Trained CNN Model As A Feature Extractor

For one of the models, we will use it as a simple feature extractor by freezing all the five convolution blocks to make sure their weights don't get updated after each epoch as we train our own model. Here, it has considered the images of dimension (229,229,3).

Also, we have assigned `include_top = False` because we are using convolution layer for features extraction and wants to train fully connected layer for our images classification (since it is not the part of Imagenet dataset). Flatten layer flattens the input as shown in Fig. 4.1. Does not affect the batch size.

```

xception = Xception(input_shape=imageSize + [3], weights='imagenet',include_top=False)

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/xcep
_kernels_notop.h5
83689472/83683744 [=====] - 1s 0us/step
83697664/83683744 [=====] - 1s 0us/step

# don't train existing weights
for layer in xception.layers:
    layer.trainable = False

# our layers - you can add more if you want
x = Flatten()(xception.output)

```

Fig. 4.1. Flattening of layer

### 4.2. Adding Dense Layers

A dense layer is a deeply connected neural network layer. It is the most common and frequently used layer. Let us create a model object named model with inputs as `xception.input` and output as dense layer as shown in Fig. 4.2.

```
prediction = Dense(5, activation='softmax')(x)

# create a model object
model = Model(inputs=xception.input, outputs=prediction)
```

Fig. 4.2. Apply Model function

The number of neurons in the Dense layer is the same as the number of classes in the training set. The neurons in the last Dense layer, use softmax activation to convert their outputs into respective probabilities.

Understanding the model is a very important phase to properly use it for training and prediction purposes. Keras provides a simple method, summary to get the full information about the model and its layers as shown in Fig. 4.3 and Fig. 4.4.

```
# view the structure of the model
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 299, 299, 3 )]	0	[]
block1_conv1 (Conv2D)	(None, 149, 149, 32 )	864	['input_1[0][0]']
block1_conv1_bn (BatchNormaliz ation)	(None, 149, 149, 32 )	128	['block1_conv1[0][0]']
block1_conv1_act (Activation)	(None, 149, 149, 32 )	0	['block1_conv1_bn[0][0]']
block1_conv2 (Conv2D)	(None, 147, 147, 64 )	18432	['block1_conv1_act[0][0]']
block1_conv2_bn (BatchNormaliz ation)	(None, 147, 147, 64 )	256	['block1_conv2[0][0]']
block1_conv2_act (Activation)	(None, 147, 147, 64 )	0	['block1_conv2_bn[0][0]']
block2_sepconv1 (SeparableConv 2D)	(None, 147, 147, 12 )	8768	['block1_conv2_act[0][0]']

Fig. 4.3. Model Summary

batch_normalization_3 (Batch Normalization)	(None, 10, 10, 1024 4096)	['conv2d_3[0][0]']
add_11 (Add)	(None, 10, 10, 1024 0)	['block13_pool[0][0]', 'batch_normalization_3[0][0]']
block14_sepconv1 (SeparableConv2D)	(None, 10, 10, 1536 1582080)	['add_11[0][0]']
block14_sepconv1_bn (Batch Normalization)	(None, 10, 10, 1536 6144)	['block14_sepconv1[0][0]']
block14_sepconv1_act (Activation)	(None, 10, 10, 1536 0)	['block14_sepconv1_bn[0][0]']
block14_sepconv2 (SeparableConv2D)	(None, 10, 10, 2048 3159552)	['block14_sepconv1_act[0][0]']
block14_sepconv2_bn (Batch Normalization)	(None, 10, 10, 2048 8192)	['block14_sepconv2[0][0]']
block14_sepconv2_act (Activation)	(None, 10, 10, 2048 0)	['block14_sepconv2_bn[0][0]']
flatten (Flatten)	(None, 204800)	['block14_sepconv2_act[0][0]']
dense (Dense)	(None, 5)	['flatten[0][0]']
=====		
Total params: 21,885,485		
Trainable params: 1,024,005		
Non-trainable params: 20,861,480		

Fig. 4.4. Model Summary summarized

### 4.3. Configure The Learning Process

The compilation is the final step in creating a model. Once the compilation is done, we can move on to the training phase. The loss function is used to find errors or deviations in the learning process. Keras requires a loss function during the model compilation process.

Optimization is an important process that optimizes the input weights by comparing the prediction and the loss function. Here we are using adam optimizer as shown in Fig. 4.5.

Metrics are used to evaluate the performance of your model. It is similar to the loss function, but not used in the training process

```
# tell the model what cost and optimization method to use
model.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)
```

Fig. 4.5. Model Optimization



#### 4.4. Train The Model

Now, let us train our model with our image dataset. The model is trained for 30 epochs and after every epoch, the current model state is saved if the model has the least loss encountered till that time. We can see that the training loss decreases in almost every epoch till 10 epochs and probably there is further scope to improve the model.

**fit\_generator** functions used to train a deep learning neural network as shown in Fig. 4.6.

##### Arguments:

- **steps\_per\_epoch**: it specifies the total number of steps taken from the generator as soon as one epoch is finished and the next epoch has started. We can calculate the value of **steps\_per\_epoch** as the total number of samples in your dataset divided by the batch size.
- **Epochs**: an integer and number of epochs used to train the model.
- **validation\_data** can be either:
  - an inputs and targets list
  - a generator
  - an inputs, targets, and sample\_weights list which can be used to evaluate the loss and metrics for any model after any epoch has ended.
- **validation\_steps**: only if the **validation\_data** is a generator then only this argument can be used. It specifies the total number of steps taken from the generator before it is stopped at every epoch and its value is calculated as the total number of validation data points in your dataset divided by the validation batch size.

```
# fit the model
r = model.fit_generator(
    training_set,
    validation_data=test_set,
    epochs=30,
    steps_per_epoch=len(training_set)//32,
    validation_steps=len(test_set)//32
)
```

Fig. 4.6. Model fit generator

The execution of the model and its corresponding accuracy is shown in Fig. 4.7

```

Epoch 1/30
3/3 [=====] - 32s 6s/step - loss: 9.6582 - accuracy: 0.4479
Epoch 2/30
3/3 [=====] - 15s 5s/step - loss: 9.3711 - accuracy: 0.5417
Epoch 3/30
3/3 [=====] - 15s 5s/step - loss: 7.4651 - accuracy: 0.5208
Epoch 4/30
3/3 [=====] - 16s 5s/step - loss: 4.8766 - accuracy: 0.5938
Epoch 5/30
3/3 [=====] - 15s 5s/step - loss: 6.3676 - accuracy: 0.6458
Epoch 6/30
3/3 [=====] - 14s 5s/step - loss: 5.2558 - accuracy: 0.6667
Epoch 7/30
3/3 [=====] - 16s 5s/step - loss: 5.4306 - accuracy: 0.6458
Epoch 8/30
3/3 [=====] - 13s 4s/step - loss: 4.8280 - accuracy: 0.6562
Epoch 9/30
3/3 [=====] - 14s 5s/step - loss: 3.9236 - accuracy: 0.6458
Epoch 10/30
3/3 [=====] - 13s 4s/step - loss: 3.2804 - accuracy: 0.6562
Epoch 11/30
3/3 [=====] - 15s 5s/step - loss: 2.1550 - accuracy: 0.6875
Epoch 12/30
3/3 [=====] - 15s 5s/step - loss: 3.0436 - accuracy: 0.6979
Epoch 13/30
3/3 [=====] - 14s 5s/step - loss: 3.4109 - accuracy: 0.7500
Epoch 14/30
3/3 [=====] - 15s 5s/step - loss: 2.8810 - accuracy: 0.7396
Epoch 15/30
3/3 [=====] - 15s 5s/step - loss: 3.4979 - accuracy: 0.6667
Epoch 16/30
3/3 [=====] - 14s 5s/step - loss: 3.1029 - accuracy: 0.6562
Epoch 17/30
3/3 [=====] - 14s 5s/step - loss: 2.8477 - accuracy: 0.6979
Epoch 18/30
3/3 [=====] - 14s 4s/step - loss: 2.6290 - accuracy: 0.6979
Epoch 19/30
3/3 [=====] - 16s 5s/step - loss: 4.5827 - accuracy: 0.5938
Epoch 20/30
3/3 [=====] - 13s 4s/step - loss: 1.7713 - accuracy: 0.7604
Epoch 21/30
3/3 [=====] - 14s 5s/step - loss: 4.1266 - accuracy: 0.6042
Epoch 22/30
3/3 [=====] - 15s 5s/step - loss: 2.2045 - accuracy: 0.7188
Epoch 23/30
3/3 [=====] - 15s 5s/step - loss: 2.7497 - accuracy: 0.7500
Epoch 24/30
3/3 [=====] - 16s 5s/step - loss: 3.3502 - accuracy: 0.7083
Epoch 25/30
3/3 [=====] - 15s 5s/step - loss: 3.1592 - accuracy: 0.7188
Epoch 26/30
3/3 [=====] - 14s 5s/step - loss: 3.2060 - accuracy: 0.6354
Epoch 27/30
3/3 [=====] - 16s 5s/step - loss: 3.4886 - accuracy: 0.6250
Epoch 28/30
3/3 [=====] - 15s 5s/step - loss: 3.0558 - accuracy: 0.6979
Epoch 29/30
3/3 [=====] - 14s 5s/step - loss: 4.7360 - accuracy: 0.6250
Epoch 30/30
3/3 [=====] - 14s 5s/step - loss: 2.0049 - accuracy: 0.7708

```

Fig. 4.7. Model accuracy



## 4.5. Save The Model

The model is saved with .h5 extension as shown in the below Fig. 4.8. An H5 file is a data file saved in the Hierarchical Data Format (HDF). It contains multidimensional arrays of scientific data.



```
model.save('Updated-xception-diabetic-retinopathy.h5')
```

Fig. 4.8 Save Model

## 1. IBM Cloud Access

Watson Studio democratizes data science and AI to drive innovation in your business. With a suite of tools for all skill levels, everyone can collaborate to prepare, analyze, and model data. You can write Python or R code in notebooks, visually code on a graphical canvas, or automatically build models. There are some features and capabilities of IBM Watson cloud as mentioned below:

1. **Speed AI development with AutoAI:** With AutoAI, beginners can build models without coding, and expert data scientists can speed up experimentation in AI development. AutoAI automates data preparation, model development, feature engineering, and hyperparameter optimization.
2. **Optimize decisions:** Decision Optimization streamlines the selection and deployment of prescriptive models. Write code in Python or OPL, or in natural language expressions with the intelligent Modeling Assistant. Investigate and compare solutions for multiple scenarios with dashboards.
3. **Develop models visually:** With the IBM SPSS Modeler graphical canvas, create a flow of steps to prepare data and build predictive models. Drag and drop from over 100 data preparation, data visualization, statistical analysis, predictive modelling, and text analytics nodes.
4. **Federated model training:** With Federated Learning, train a model on a set of federated data sources while maintaining data security. Each participating party in the federation trains the common machine learning model without moving or sharing data. The training results are fused into a more accurate model.

### 5.1. Register & Login To IBM Cloud

#### Create Service Instance

- Log in to your IBM Cloud account, and click on Catalog as shown in Fig. 5.1.

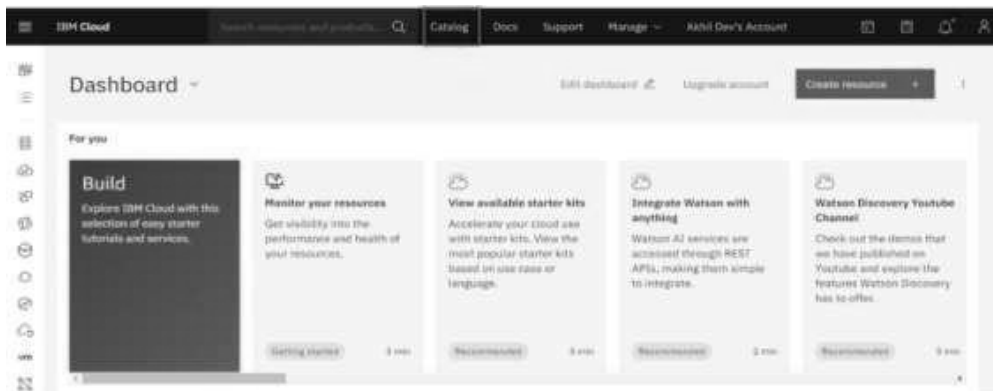


Fig. 5.1. IBM cloud account

- Type Cloudant in the Search bar and click to open it as shown in Fig. 5.2.

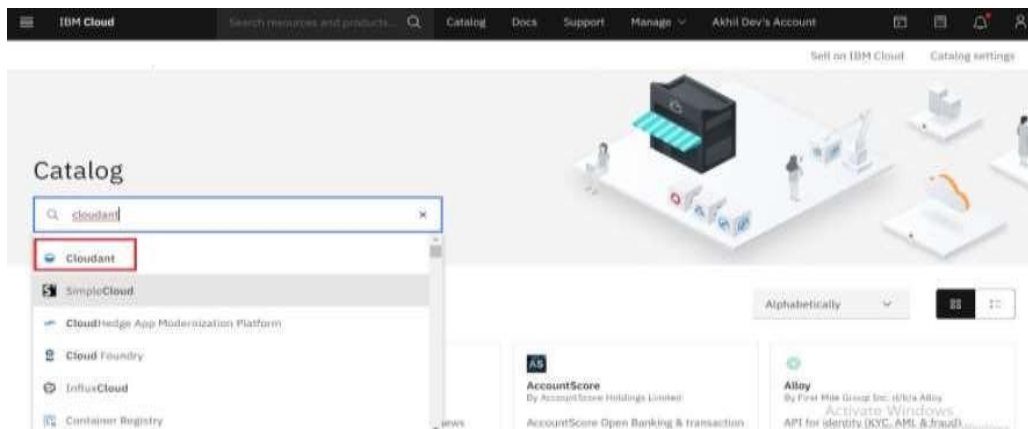


Fig. 5.2 Search in Cloudant Catalog

- Select an offering and an environment as shown in Fig. 5.3.

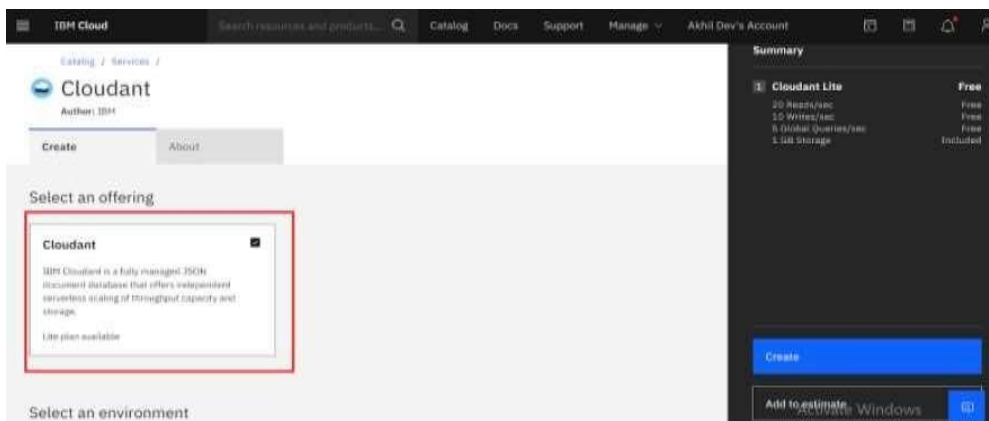


Fig. 5.3 Select Environment

- Select region as Dallas & Type an instance name then click on create service as shown in Fig. 5.4.

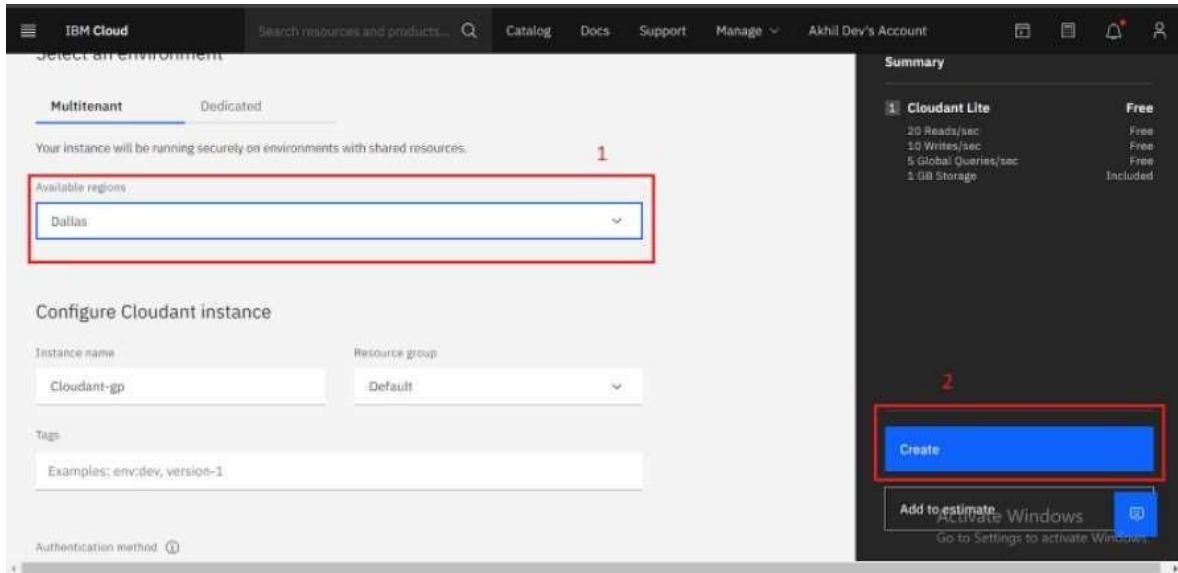


Fig. 5.4 Select Region and click on create

After clicking on create, the system displays a message to say that the instance is being provisioned, which returns to the Resource list. From the Resource list, it displays the status for the current instance is, Provision in progress. When the status changes to Active, click the instance.

## 5.2. Creating Service Credentials

1. To create the connection information that application needs to connect to the instance, click on New credential as shown in Fig. 5.5.

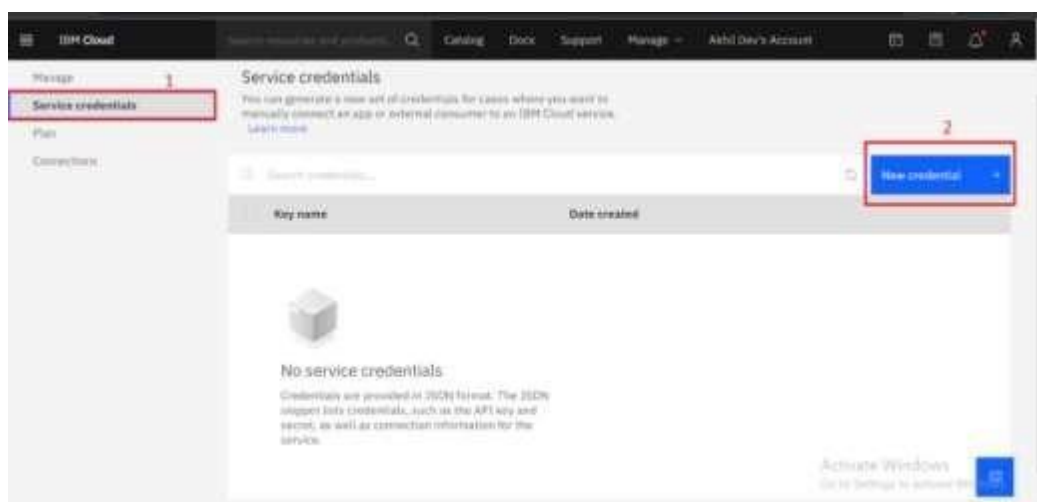


Fig. 5.5 Connection creation

2. Enter a name for the new credential in the Add new credential window.
3. Accept the Manager role.

4. Create a service ID or have one automatically generated for the user.
5. Add inline configuration parameters. This parameter isn't used by IBM Cloudant service credentials, so ignore it. Click Add as shown in Fig. 5.6.

**Create credential**

Name:

Role:

[Advanced options](#)

Select Service ID (Optional):

Provide service-specific configuration parameters in a valid JSON object (Optional)

Add inline configuration parameters (Optional)

Fig. 5.6 Account credentials

### 5.3. Launch Cloudant DB

Launch the Cloudant DB by clicking on the Launch Dashboard as shown in Fig. 5.7.

Resource list / **Cloudant-4k** Active [Add tags](#)

**Manage** Overview Capacity Docs

Service credentials

Plan

Connections

**Deployment details**

CRN: crn:v1:bluemix:public:cloudantnosqldb:us-south:a/0a6de0ab44cc4fcb6b5a62b2fec15f6:18c5f94d-d92f-46d0-9b52-5596e5cbb0d2::

Location: Dallas

External endpoint: <https://2eb40045-a8d6-450d-9d24-52cc7cbb2810-bluemix.cloudant.com>

External endpoint (preferred): <https://2eb40045-a8d6-450d-9d24-52cc7cbb2810-bluemix.cloudantnosqldb.appdomain.cloud>

Fig. 5.7. Launch Cloudant DB

Note: If it is a New User then it will show an empty database otherwise it will list already existing DB as shown in Fig. 5.8.



Fig. 5.8 Home page of Cloudant DB

## 5.4. Create Database

In order to manage a connection from a local system, it must first initialize the connection by constructing a Cloudant client. We need to import the cloudant library.

```
from cloudant.client import Cloudant
#authentication using an IAM Apikey
client = Cloudant.iam('username', 'apikey', connect= True)
```

IBM Cloud Identity & Access Management enables you to securely authenticate users and control access to all cloud resources consistently in the IBM Bluemix Cloud Platform. In the above cloudant.iam() method we have to give username & apikey to build the connection with cloudant DB as shown in Fig. 5.9.

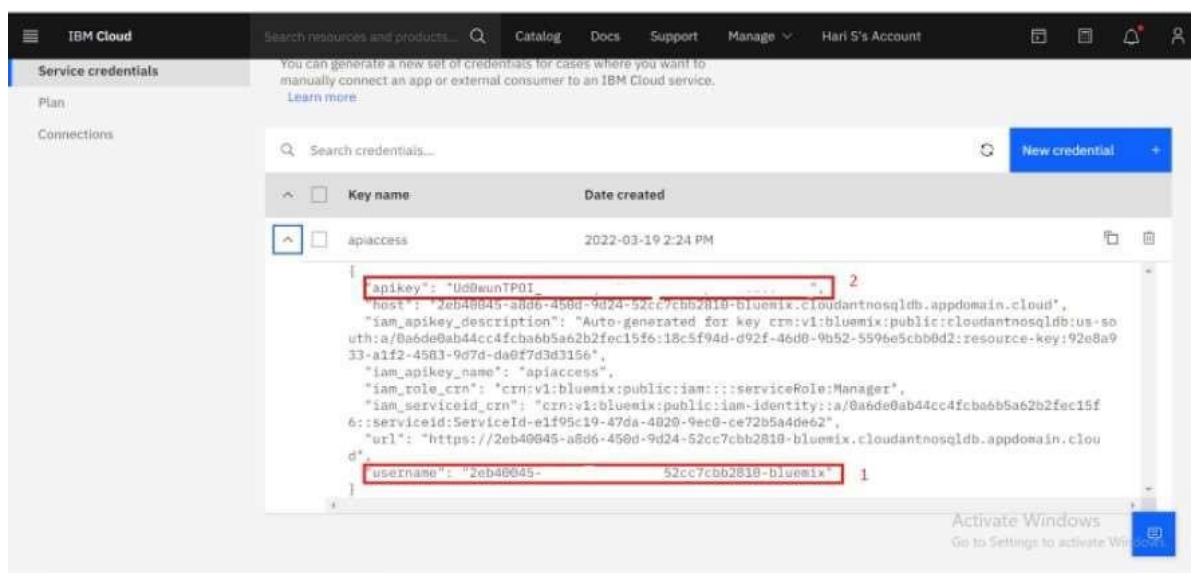


Fig. 5.9. Access the Username and API key

Once a connection is established you can then create a database, open an existing database. Create a database as my\_database.

```
# Create a database using an initialized client
my_database = client.create_database('my_database')
```

## 6 Application Building

In this section, a web application is built that is integrated to the model built earlier. A UI is provided to the user where he can upload the image. Based on the saved model, the uploaded image will be analyzed and prediction is showcased on the UI.

This section has the following tasks

- Building HTML Pages
- Building server side script

### 6.1. Building Html Pages

For this project create one HTML file namely, index.html and save them in the templates folder. The outcome index.html page look is shown in Fig. 6.1.

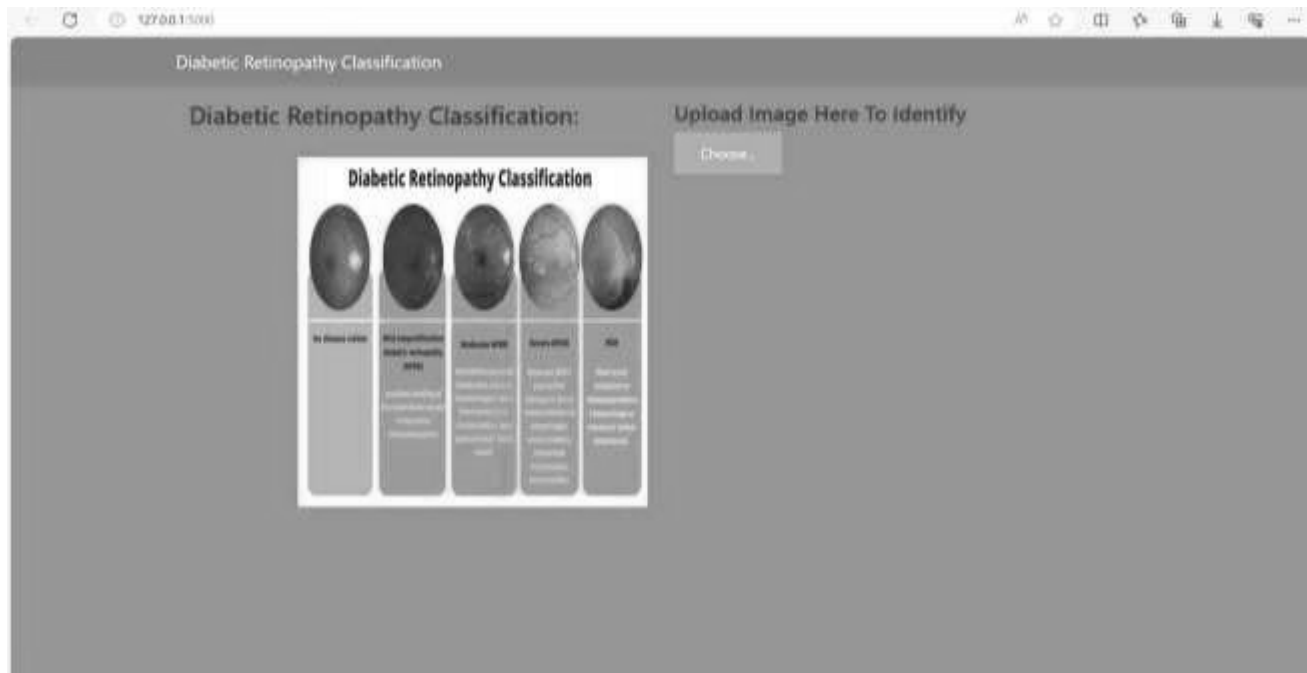
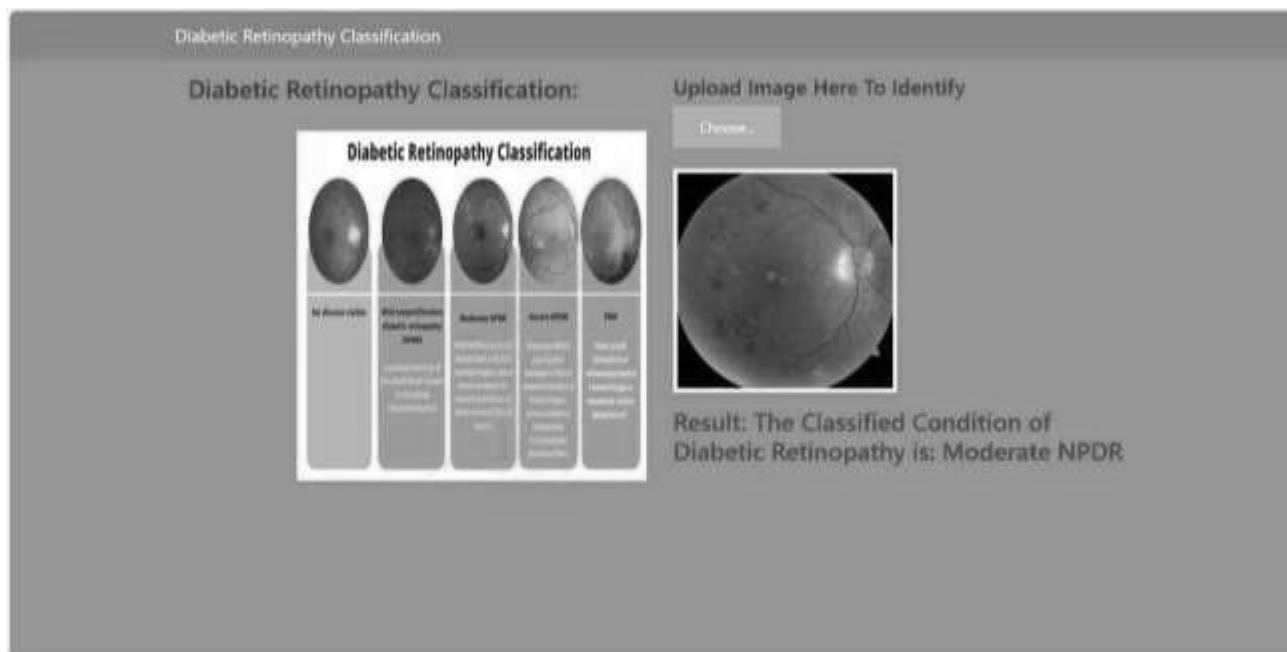


Fig. 6.1. Home page of Diabetic Retinopathy Classification Webpage

Now click on choose button to select the image to predict the type of diabetic condition as shown in Fig. 6.2.



Fig. 6.2 Select an image to predict the type of diabetic condition.



After the successful upload of the image, press the submit button to print the class of diabetes of the concerned person. The prediction button is shown below the image as shown in Fig. 6.3.

Fig. 6.3 Prediction button to print the result.

## 6.2. Build Python Code

Import the required libraries for running the project. Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (`_name_`) as argument.



Fig. 6.4. Building python code in PyCharm

Here we will be using a declared constructor to route to the HTML page which we have created earlier as shown in Fig. 6.4.

In the above example, '/' URL is bound with the home.html function. Hence, when the home page of the web server is opened in the browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

### Showcasing prediction on UI:

The image is selected from uploads folder. Image is loaded and resized with load\_img() method. To convert image to an array, img\_to\_array() method is used and dimensions are increased with expand\_dims() method. Input is processed for xception model and predict() method is used to predict the probability of classes. To find the max probability np.argmax is used.

### Main Function:

```

if __name__ == "__main__":
    app.run(debug=False)

```

### Run The Application

- Open anaconda prompt from the start menu
- Navigate to the folder where your python script is.
- Now type “python app.py” command



- Navigate to the localhost where you can view your web page.
- Click on the predict button from the top right corner, enter the inputs, click on the submit button, and see the result/prediction on the web.

## 7. Result and Discussion

### 7.1. Run the application

In the anaconda prompt, navigate to the folder in which the flask app is present. When the python file is executed the localhost is activated on 5000 port and can be accessed through it as shown in Fig. 7.1.

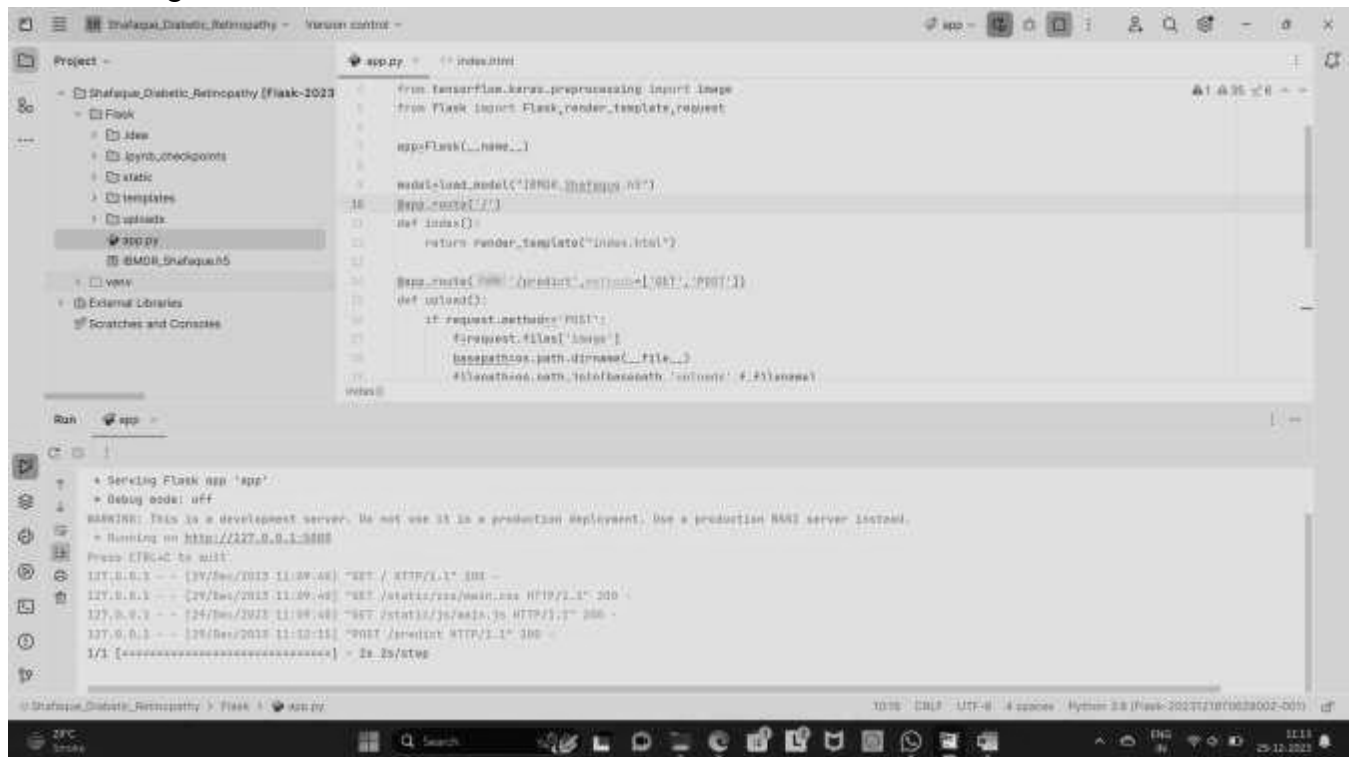


Fig. 7.1. Running the flask application.

Open the browser and navigate to localhost: 5000 to check your application

The final home page displayed after building python code and running the flask application on visual code is shown in Fig. 7.2.



Fig. 7.2. Select an image to predict the class of DR.

After successfully loading of the prediction page where it is showing choose button to upload the image to predict the outcomes as shown in Fig. 7.3.

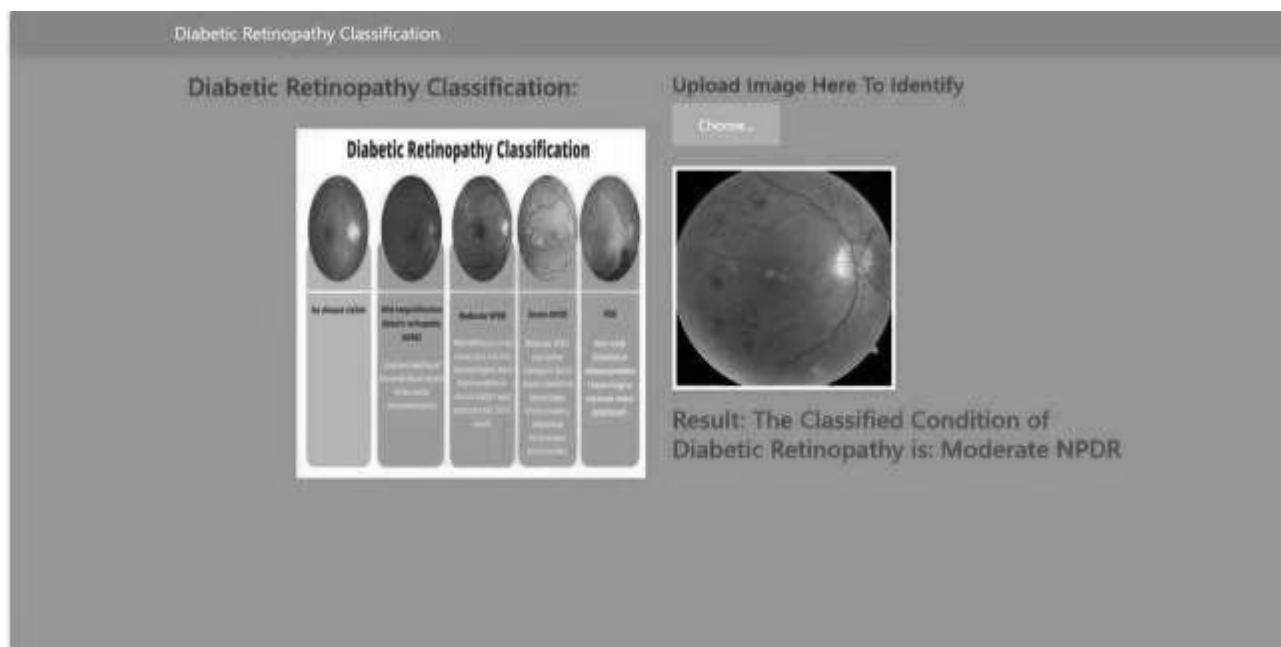


Fig. 7.3 Predict the outcome of selected image

## 8. ADVANTAGES & DISADVANTAGES

For image recognition, image classification and computer vision (CV) applications, CNNs are particularly useful because they provide highly accurate results, especially when a lot of data is involved. The CNN also learns the object's features in successive iterations as the object data moves through the CNN's many layers. This direct (and deep) learning eliminates the need for manual feature extraction (feature engineering). CNNs can be retrained for new recognition tasks and built on preexisting networks. These advantages open up new opportunities to use CNNs for real-world applications without increasing computational complexities or costs. The downside of CNN is that it requires large amounts of data. High computational cost causes hard to optimize due to large parameter size.

## 9. Applications

The most common applications of above project are as follows:

- **Healthcare application:** It can examine thousands of visual reports to detect any anomalous conditions in patients, such as type of Diabetes.
- **Automotive:** It is powering research into autonomous health care system.
- 
- **E-medical:** It provides platform that incorporate visual search allow smart system to recommend medication.
- **AutoML processing of CNNs:** In autoML assistants learn and process the model is updated automatically and predict more accurate results.

## 10. Conclusion

DR in diabetics prevents the worsening of DR. However, the CNN classification model should be used as supplements to a healthy and balanced health and prevents all the complications of diabetes. In conclusion, the data presented in this model strongly gives 80% accuracy to identify the classification of DR thus improving the quality of life of millions of diabetics. The

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