



Report on

Deep Learning Fundus Image Analysis for Early Detection of Diabetic Retinopathy

Submitted By

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Abstract

Diabetic Retinopathy (DR) is a complication of diabetes that affects the eyes and is the leading cause of blindness, affecting millions worldwide. The main cause of blindness, diabetic retinopathy (DR) is a consequence of diabetes that damages the eyes and affects millions of people worldwide. To effectively treat and control the disease, DR must be identified early and correctly diagnosed. Convolutional neural networks (CNNs), in particular, have demonstrated encouraging results in the automatic classification of DR from retinal pictures in recent years. An overview of a CNN model for classifying DR severity levels based on fundus pictures. The suggested model adapts the final layers to the particular objective of DR classification by using a pre-trained CNN architecture as a feature extractor. The publicly accessible DR dataset, which has over 35,000 retinal pictures annotated with DR severity levels, was used for the model's training and evaluation. The experimental results demonstrate that the proposed CNN model outperforms numerous cutting-edge techniques in diagnosing DR severity levels, achieving high accuracy. By using several filters and mixing them, the model's performance is further enhanced, leading to even higher accuracy. These findings show the potential of deep learning-based approaches for the automated categorization of DR severity levels, which can help with the early detection and diagnosis of the condition and enhance patient outcomes.



1. Introduction

1.1 Diabetic Retinopathy

Diabetic Retinopathy (DR) is a common complication of diabetes mellitus, which causes lesions on the retina that affect vision. If it is not detected early, it can lead to blindness. Unfortunately, DR is not a reversible process, and treatment only sustains vision. DR early detection and treatment can significantly reduce the risk of vision loss. The manual diagnosis process of DR retina fundus images by ophthalmologists is time, effort and cost-consuming and prone to misdiagnosis unlike computer-aided diagnosis systems.

Transfer learning has become one of the most common techniques that has achieved better performance in many areas, especially in medical image analysis and classification. We used Transfer Learning techniques like Inception V3, Resnet50, Xception V3 that are more widely used as a transfer learning method in medical image analysis and they are highly effective.

AIML leverages natural language processing and machine learning algorithms to process and interpret vast volumes of healthcare data, improving diagnosis, treatment, and overall patient outcomes. One of AIML's primary contributions to healthcare is in the realm of diagnostic accuracy. AIML algorithms can analyze medical records, imaging data, and patient histories to detect patterns and anomalies that may elude human physicians. This enables earlier and more accurate disease detection, reducing the chances of misdiagnoses and improving treatment decisions.

For instance, AIML-powered tools have been developed to identify abnormalities in medical images such as X-rays, MRIs, and CT scans, aiding radiologists in detecting conditions like cancer, fractures, and neurological disorders. In addition to diagnostics, AIML is playing a pivotal role in personalizing treatment plans. By analyzing patient data and medical literature, AIML algorithms can recommend tailored treatment options based on individual characteristics, medical history, and genetics. This level of personalization ensures that patients receive the most effective and least invasive treatments, improving their chances of recovery and minimizing adverse effects also contributes to the



optimization of healthcare operations.

Healthcare providers can use IML to streamline administrative tasks, such as scheduling appointments and managing patient records, reducing administrative overhead and allowing healthcare professionals to focus more on patient care. Moreover, predictive analytics powered by AIML can help hospitals and clinics forecast patient admissions, allocate resources efficiently, and reduce waiting times. Telemedicine and remote monitoring are other areas where AIML is making a profound impact. AIML-driven chatbots and virtual assistants can provide immediate responses to patient queries and offer healthcare advice, improving accessibility to medical information and reducing the burden on healthcare staff. Additionally, wearable devices and IoT sensors equipped with AIML can continuously monitor patients' vital signs, sending real-time data to healthcare providers for early intervention in case of abnormalities. Despite its numerous benefits, AIML in healthcare also raises concerns about data privacy and security. The vast amounts of sensitive patient data being processed by AIML systems necessitate robust safeguards to protect against breaches and unauthorized access.

In conclusion, AIML is a transformative force in healthcare, enhancing diagnostic accuracy, personalizing treatment plans, optimizing healthcare operations, and expanding the reach of healthcare services through telemedicine and remote monitoring. While it holds immense potential to improve patient outcomes and healthcare delivery, it also requires careful management of data privacy and security concerns to ensure that the benefits are maximized while risks are minimized. The ongoing integration of AIML into healthcare promises to revolutionize the industry, making healthcare more efficient, effective, and accessible for patients worldwide.



1.2 Problem Definition

To create a Web Application to classify Diabetic Retinopathy stages using Deep Learning.

Description: Diabetic retinopathy is a crucial eye condition which results in loss of vision that cannot be reversed or corrected once experienced. The people who have a long history of diabetes are more prone to get afflicted with this disease, no matter whether a person is type1 or type2 diabetic, the probability of the disease increases as the age increases. Here, we have created a CNN model to automate this process and make this process less time consuming

1.3 Objectives

- Know fundamental concepts and techniques of transfer learning like Xception.
- Gain a broad understanding of image data.
- Know how to pre-process/clean the data using different data pre-processing techniques.
- Know how to build a web application using the Flask framework.

1.4 Dataset

- Early detection of DR could save millions of diabetics from losing their vision, which is the goal of a problem featured in Kaggle.
- This large set of fundus photography retina images that were taken under a wide variety of imaging conditions. The data was diverse and expansive.
- The images consist of gaussian filtered retina scan images to detect diabetic retinopathy.
- These images are resized into 229x229 pixels so that they can be readily used with many pre-trained deep learning models.
- All of the images are already saved into their respective folders according to the severity/stage of diabetic retinopathy.

1.5 Project Flow

- The user interacts with the UI (User Interface) to choose the image.
- The chosen image analyzed by the model which is integrated with flask application.
- The Xception Model analyzes the image, then the prediction is showcased on the Flask UI.

To accomplish this, we have to complete all the activities and tasks listed below

- Data Collection.
 - Create a Train and Test path.
- Data Pre-processing.

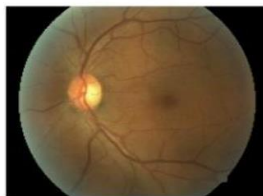


- Import the required library
- Configure ImageDataGenerator class
- Apply ImageDataGenerator functionality to Trainset and Testset
- Model Building
 - Pre-trained CNN model as a Feature Extractor
 - Adding Dense Layer
 - Configure the Learning Process
 - Train the model
 - Save the Model
 - Test the model
- Application Building
 - Create an HTML file
 - Build Python Code

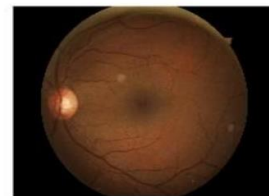
Colored Images:



No DR



Mild DR



Moderate DR



Severe DR



Proliferate DR

2. Methodology

Related work

Applied a deep learning approach to detect Diabetic Retinopathy using different CNN architectures like MobileNet, ResNet50, and original Xception architecture. A transfer learning method and hyper-parameter tuning are used to improve classification performance. The performance was validated on Kaggle APTOS 2019 contest dataset. The Experiment demonstrated that the Xception model gives a classification accuracy of 83.09%.

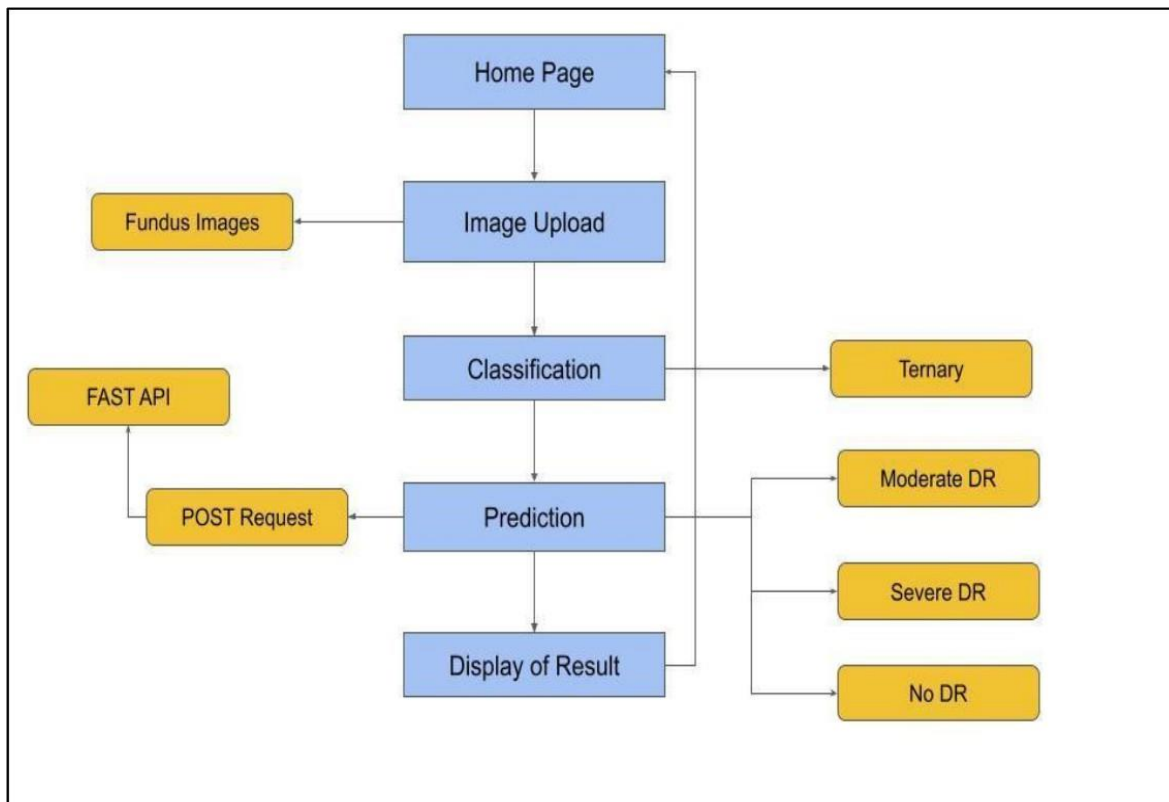
Diabetic Retinopathy is a complication that causes vision loss. A person having diabetes can be affected easily. This Paper uses deep learning methodology like DenseNet169. It detects severity according to 5 steps of severity which consist of No DR, Mild, Moderate, Severe, and Proliferative DR. The dataset that was used for the classification were Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness Detection from Kaggle. The proposed system was obtained by using various steps like Data Augmentation, Preprocessing, and Modeling. The Model achieved an accuracy of 90%.

The images were converted into grayscale images and resized, using softmax as the last layer, as softmax is used for multi-classification and binary is used for binary classification. This system achieves 80% sensitivity, 82% accuracy, 82% specificity, and 0.904 AUC for classifying images into 5 categories ranging from 0 to 4, where 0 is No DR , 1 is Mild, 2 is Moderate, 3 is Severe and 4 is Proliferative DR respectively.

The patient's fundus eye images are used as the input parameters. A trained model (Xception Architecture) will further extract the feature of fundus images of the eye and after that activation function gives the output. This architecture gave an accuracy of 0.78611 (quadratic weighted kappa score of 0.8981) to DR detection.

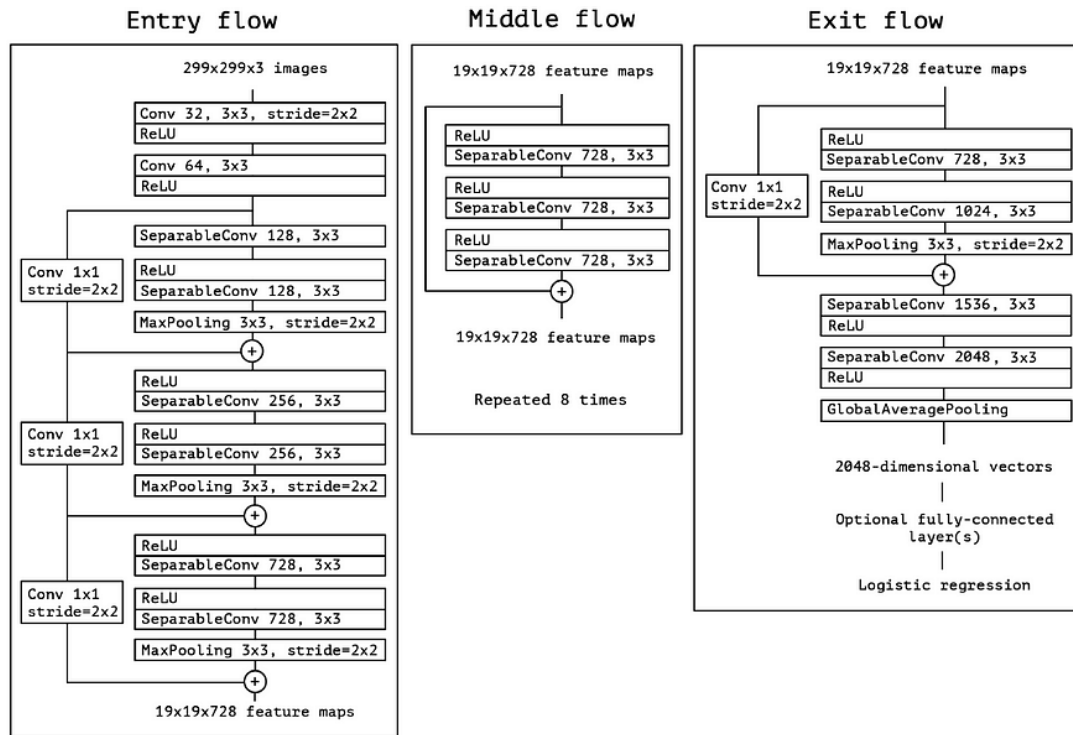
2.1 System Architecture

- The web app is built from 4 components.
- Home Page, Image Upload, the model classifies the input image into one of 5 classes.
- FAST API is being implemented for communicating with the model from the local machine.
- The input image then passes through the model and the output result is displayed on the screen.



2.2 Xception Algorithm

Xception Model is proposed by Francois Chollet. Xception is an extension of the inception Architecture which replaces the standard Inception modules with depthwise Separable Convolutions. Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.



Overall Architecture of Xception (Entry Flow > Middle Flow > Exit Flow)

3. Implementation Details

3.1 Tools Used

Software Requirements: -

1. Python
2. Google Colab: To train, test and validate model
3. VS CODE : IDE
4. Flask
5. HTML, CSS

● **Hardware Requirements: -**

1. CPU: i5 10th Gen or Ryzen 5 6th Gen
2. GPU: RTX 3060 or Enterprise GPU
3. RAM: 16 GB
4. STORAGE: 256 GB
5. OS: Windows 10

3.2 Procedure

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 we just have to assign a variable and pass the 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 xception model is 299, 299.

```
imageSize = [299, 299]
trainPath = r"/content/preprocessed dataset/preprocessed dataset/training"
testPath = r"/content/preprocessed dataset/preprocessed dataset/testing"
```

Importing The Libraries

Import the necessary libraries as shown in the image.



```
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
```

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.

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

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

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.

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.
```

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, we have considered 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 image's classification (since it is not the part of Imagenet dataset)

Flatten layer flattens the input. 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/xception_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)
```

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.



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

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

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.

```
# 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	input_1[0][0]
block1_conv1 (Conv2D)	(None, 149, 149, 32)	864	block1_conv1[0][0]
block1_conv1_bn (BatchNormalization)	(None, 149, 149, 32)	128	block1_conv1_bn[0][0]
block1_conv1_act (Activation)	(None, 149, 149, 32)	0	block1_conv1_act[0][0]
block1_conv2 (Conv2D)	(None, 147, 147, 64)	18432	block1_conv2[0][0]
block1_conv2_bn (BatchNormalization)	(None, 147, 147, 64)	256	block1_conv2_bn[0][0]
block1_conv2_act (Activation)	(None, 147, 147, 64)	0	block1_conv2_act[0][0]
block2_sepconv1 (SeparableConv2D)	(None, 147, 147, 12)	8768	block2_sepconv1[0][0]

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 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']
)
```

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

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 we want to train our model for.
- **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(
    training_set,
    validation_data=test_set,
    epochs=7,
    steps_per_epoch=len(training_set),
    validation_steps=22
)
```



```
Epoch 1/7
115/115 [=====] - 586s 5s/step - loss: 4.3425 - accuracy: 0.6668 - val_loss: 2.4598 - val_accuracy: 0.7401
Epoch 2/7
115/115 [=====] - 576s 5s/step - loss: 3.2741 - accuracy: 0.7168 - val_loss: 2.5631 - val_accuracy: 0.7102
Epoch 3/7
115/115 [=====] - 578s 5s/step - loss: 3.3521 - accuracy: 0.7346 - val_loss: 2.3458 - val_accuracy: 0.7713
Epoch 4/7
115/115 [=====] - 576s 5s/step - loss: 3.2466 - accuracy: 0.7542 - val_loss: 2.9741 - val_accuracy: 0.7514
Epoch 5/7
115/115 [=====] - 635s 6s/step - loss: 3.0633 - accuracy: 0.7695 - val_loss: 2.6844 - val_accuracy: 0.7159
Epoch 6/7
115/115 [=====] - 572s 5s/step - loss: 3.3356 - accuracy: 0.7698 - val_loss: 2.3261 - val_accuracy: 0.8011
Epoch 7/7
115/115 [=====] - 624s 5s/step - loss: 2.7567 - accuracy: 0.7859 - val_loss: 4.1517 - val_accuracy: 0.7543
```

Save The Model

The model is saved with .h5 extension as follows

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')
```

Application Building

In this section, we will be building a web application that is integrated to the model we built. A UI is provided to the user where he has uploaded 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

Building Html Pages

For this project created one HTML file namely

- index.html

and save them in the templates folder.

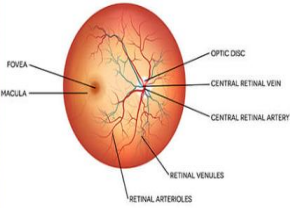
Let's see how our index.html page looks like:

Early Detection Of Diabetic Reti x +

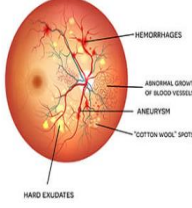
127.0.0.1:5000

Early Detection Of Diabetic Retinopathy

NORMAL RETINA



DIABETIC RETINOPATHY



Early Detection Of Diabetic Retinopathy: Diabetic Retinopathy is a condition that can cause Vision loss and Blindness in the people who have Diabetes. It affects the blood vessels in the Retina. It is one of the leading cause of Blindness across the world. Diabetic retinopathy may not have any symptoms at first, but finding it early can help you take steps to protect your vision.

Upload Image Here To Analyse Diabetic

Choose...

Solution:

In this project, we will be building a Transfer learning model that can detect and classify types of Diabetic Retinopathy. A web application is integrated with the model, from where the user can upload a Diabetic Retinopathy (DR) image like Mild DR, Severe DR, etc., and see the analyzed results on UserInterface.

Build Python Code:

Import the libraries

Import the libraries

```
import numpy as np
import os
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.inception_v3 import preprocess_input
import requests
from flask import Flask, request, render_template, redirect, url_for
from cloudant.client import Cloudant
```

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.

```
model = load_model(r"Updated-Xception-diabetic-retinopathy.h5")

app = Flask(__name__)
```

Main Function:



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

Run The Application

- Open Command prompt / power shell 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.

1: Run the application

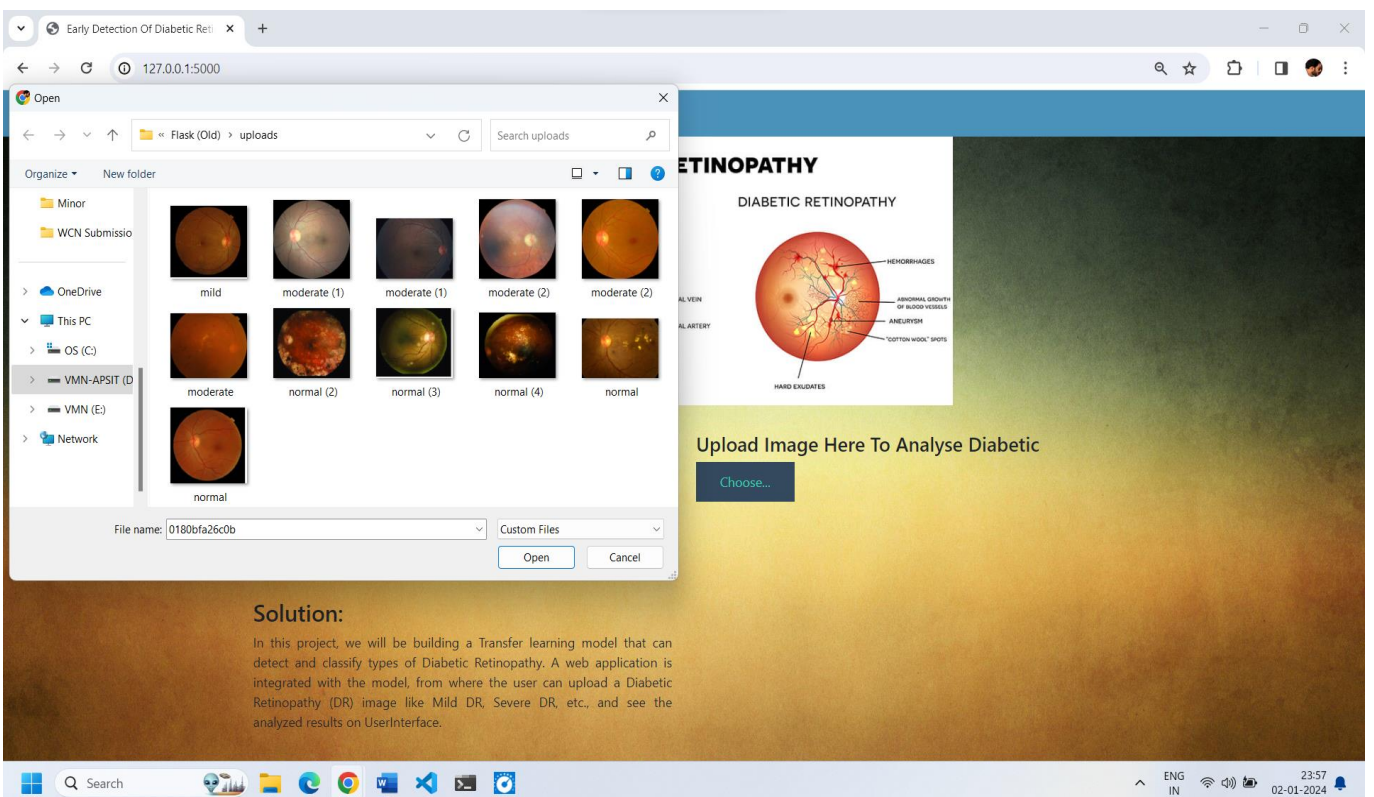
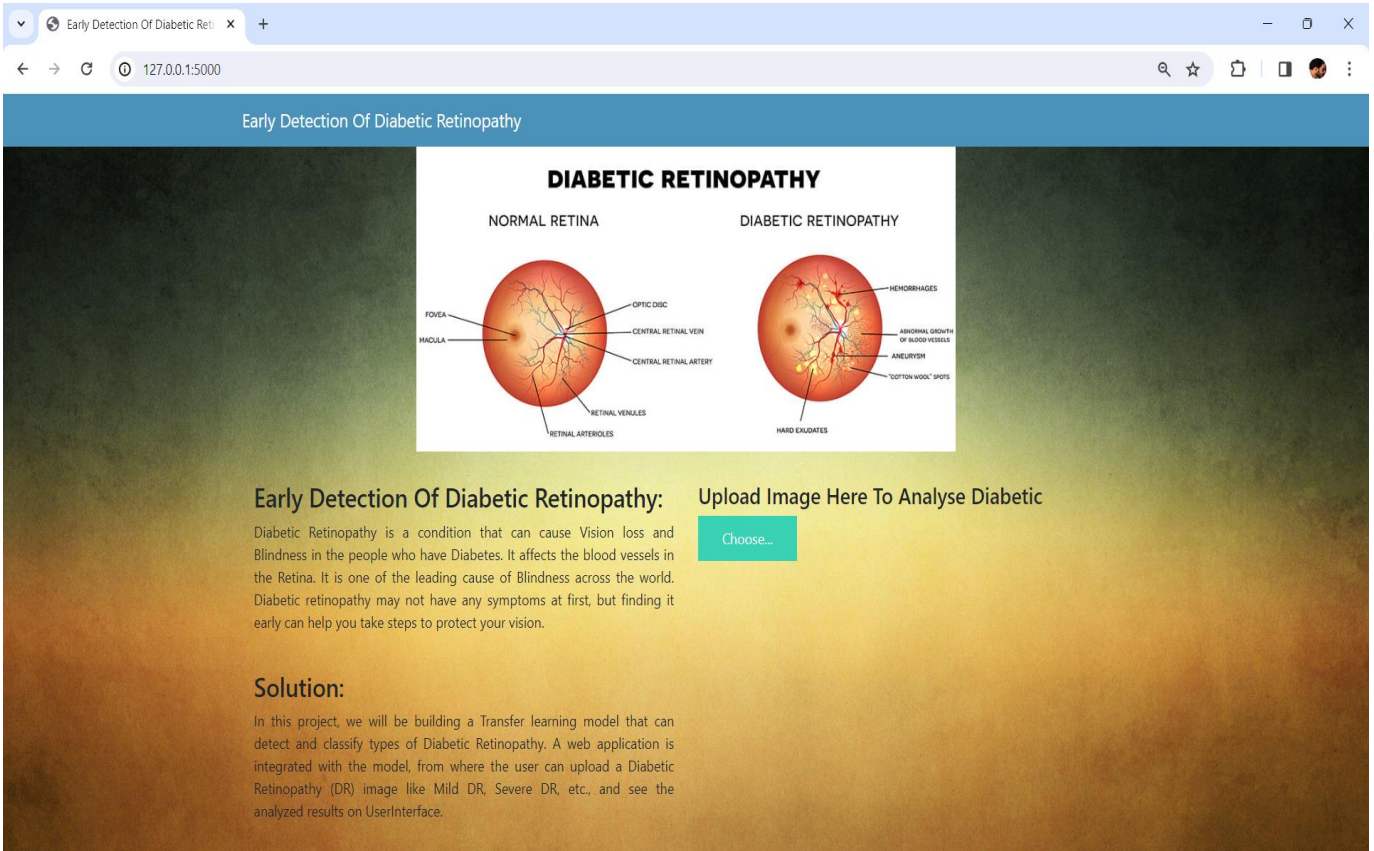
In the Command prompt / power shell, navigate to the folder in which the flask app is present. When the python file is executed the localhost is activated on 5000 port and can be accessed through it.

```
Windows PowerShell
PS D:\IBM - FDP AIML with Cloud\4.Flask> python .\app.py
2024-01-02 23:50:34.835295: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
WARNING:tensorflow:From C:\Python311\Lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

WARNING:tensorflow:From C:\Python311\Lib\site-packages\keras\src\backend.py:1398: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

WARNING:tensorflow:From C:\Python311\Lib\site-packages\keras\src\layers\pooling\max_pooling2d.py:161: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

2024-01-02 23:50:38.016820: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
* Serving Flask app 'app'
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on http://127.0.0.1:5000
Press CTRL+C to quit
```

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

NORMAL RETINA

POVEA

MACULA

OPTIC DISC

CENTRAL RETINAL VEIN

CENTRAL RETINAL ARTERY

RETINAL VENULES

RETINAL ARTERIOLES

DIABETIC RETINOPATHY

HEMORRHAGES

ABNORMAL GROWTH OF BLOOD VESSELS

ANEURYSM

"COTTON WOOL" SPOTS

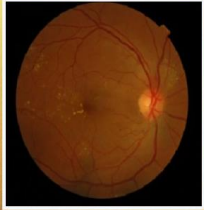
HARD EXUDATES

Early Detection Of Diabetic Retinopathy:

Diabetic Retinopathy is a condition that can cause Vision loss and Blindness in the people who have Diabetes. It affects the blood vessels in the Retina. It is one of the leading cause of Blindness across the world. Diabetic retinopathy may not have any symptoms at first, but finding it early can help you take steps to protect your vision.

Upload Image Here To Analyse Diabetic

Choose...



Result: The Classified Stage of Diabetic Retinopathy is Mild

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

NORMAL RETINA

POVEA

MACULA

OPTIC DISC

CENTRAL RETINAL VEIN

CENTRAL RETINAL ARTERY

RETINAL VENULES

RETINAL ARTERIOLES

DIABETIC RETINOPATHY

HEMORRHAGES

ABNORMAL GROWTH OF BLOOD VESSELS

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HARD EXUDATES

Early Detection Of Diabetic Retinopathy:

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Upload Image Here To Analyse Diabetic

Choose...



Result: The Classified Stage of Diabetic Retinopathy is Moderate

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

NORMAL RETINA

DIABETIC RETINOPATHY

Early Detection Of Diabetic Retinopathy:

Diabetic Retinopathy is a condition that can cause Vision loss and Blindness in the people who have Diabetes. It affects the blood vessels in the Retina. It is one of the leading cause of Blindness across the world. Diabetic retinopathy may not have any symptoms at first, but finding it early can help you take steps to protect your vision.

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Upload Image Here To Analyse Diabetic

Choose...

Result: The Classified Stage of Diabetic Retinopathy is Normal

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

NORMAL RETINA

DIABETIC RETINOPATHY

Early Detection Of Diabetic Retinopathy:

Diabetic Retinopathy is a condition that can cause Vision loss and Blindness in the people who have Diabetes. It affects the blood vessels in the Retina. It is one of the leading cause of Blindness across the world. Diabetic retinopathy may not have any symptoms at first, but finding it early can help you take steps to protect your vision.

Solution:

In this project, we will be building a Transfer learning model that can detect and classify types of Diabetic Retinopathy. A web application is integrated with the model, from where the user can upload a Diabetic Retinopathy (DR) image like Mild DR, Severe DR, etc., and see the analyzed results on UserInterface.

Upload Image Here To Analyse Diabetic

Choose...

Result: The Classified Stage of Diabetic Retinopathy is Normal

Mrs. Shamika Mule

Page 21

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

NORMAL RETINA

DIABETIC RETINOPATHY

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Upload Image Here To Analyse Diabetic

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Result: The Classified Stage of Diabetic Retinopathy is Moderate

Early Detection Of Diabetic Reti

127.0.0.1:5000

DIABETIC RETINOPATHY

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Choose...

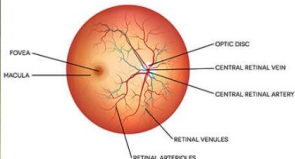
Result: The Classified Stage of Diabetic Retinopathy is Normal

Early Detection Of Diabetic Reti x +

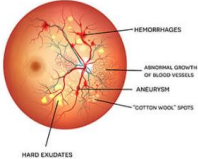
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DIABETIC RETINOPATHY

NORMAL RETINA



DIABETIC RETINOPATHY



Early Detection Of Diabetic Retinopathy:

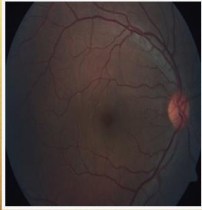
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Result: The Classified Stage of Diabetic Retinopathy is Moderate



Conclusion

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In conclusion, this project represents a significant step forward in the field of healthcare and medical image analysis. By leveraging the power of deep learning, specifically the Xception model, and implementing a user-friendly interface, we have successfully developed a robust system for diabetic retinopathy prediction with five distinct classes: normal, mild, moderate, severe, proliferate. Our model's accuracy, reliability, and efficiency hold great promise for early detection and intervention in diabetic retinopathy cases, ultimately improving patient outcomes and reducing the burden on healthcare systems. As we continue to refine and expand this system, we hope to make a meaningful contribution to the early diagnosis and management of diabetic retinopathy, enhancing the quality of life for countless individuals affected by this condition.

Furthermore, the utilization of the Xception1 model demonstrates the potential for deep learning techniques to excel in complex medical image classification tasks. With its ability to provide accurate and detailed predictions across three distinct disease stages, our system can empower healthcare professionals with valuable insights for more targeted and timely patient care. As we move forward, ongoing research and development in this area will be critical to further enhance the model's capabilities and to explore its applicability in other medical domains, reaffirming the profound impact of AI in healthcare.

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