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Diabetic Retinopathy Prediction using Modified Inception V3 Model Structure

Shwetha G.K[1] ,Udaya Kumar Reddy K R[2] ,Jayantkumar.A.Rathod[3] , Sathyaprakash B.P[4], Lolakshi P K

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Abstract: The analysis of clinical findings revealed that more than 10% of diabetic individuals have an elevated risk of eye issues. Diabetic Retinopathy (DR) is a type of eye illness that impacts 80-85% of persons suffering for more than 10 years from diabetes. In hospitals, retinal fundus images are commonly employed for the identification and study of diabetic retinopathy. The unprocessed retinal fundus images are difficult for machine learning approaches to analyze. Original retinal fundus images are pre-processed utilizing green channel separation, histogram equalization, contrast enhancement, and scaling procedures. For statistical analysis, 14 attributes are additionally collected from preprocessed images. Technique for the detection of retinal lesions can aid in the earlier identification and treatment of a frequently found condition, diabetic retinopathy. We introduce a new criterion for the identification of the optic disc in which we initially identify the significant blood vessels and then utilize their intersection to estimate the position of the optic disc. Future localized utilizing color characteristics. We also demonstrate that a set of attributes, including blood vessels, mucus, micro aneurysms, and hemorrhages, may be recognized with high precision utilizing different morphological techniques applied suitably.

Keywords: *Diabetic Retinopathy (DR), Retinal Fundus Images, Histogram Equalization, Contrast Enhancement, Optic disc, Morphological Techniques.*

1.Introduction

Diabetic Retinopathy is a consequence of diabetes impacts person's eyesight may decline progressively owing to injury to the retinal blood vessels. Initially, diabetic retinopathy may produce no signs or just mild vision issues. However, it can cause blindness. Patients having forms of type 1 or type 2 diabetes can get the disease. In past few years, increase in patients having diabetic dealing from diabetic retinopathy has risen exponentially (DR). DR is among the commonly found serious conditions and the biggest reason for loss of vision in average-aged persons in affluent countries. DR manifests as minute alterations in the retinal capillaries. The earliest noticeable abnormalities are micro aneurysms, which are small capillary disturbances. Micro aneurysms that are distorting produce intraregional hemorrhage. Therefore rises in the early phase of DR, often termed as moderate non-proliferative diabetic retinopathy. Owing to the susceptibility of the eye fundus to certain muscles disorders, fundus imaging is ideally suited for non-invasive visibility. The effectiveness of the testing procedure is straight proportional to the effective and precision of the images of fundus collection methodology and the image processing technologies used to identify anomalies.

NMAM Institute of Technology , Affiliated to NITTE (Deemed to be University) , India
School of Engineering, Dayananda Sagar University , Bengaluru, India
Alva's Institute of Engineering & Technology , Moodubidire , India
School of Electronics and Communication Engineering,REVA University,Bengaluru,India
Alva's Institute of Engineering & Technology , Moodubidire , India
gk.shwetha@gmail.com, udayareddykr@gmail.com, jayantkumarrathod@gmail.com pnsathyaprakash@gmail.com, lolakshi88@gmail.com
Corresponding Author : gk.shwetha@gmail.com

Intermediate non-proliferative diabetic retinopathy is characterized by the appearance of exudates, which are essentially greasy deposits oozing from the bad end of blood vessels. If these secretions begin to grow in the central vision region, the condition is known as diabetic maculopathy. Later with specific period of duration, when retinopathy progresses, the micro infarcts in the retina block the blood arteries. These little infarcts are referred to as delicate exudates. When all three of the above irregularities are present, this type of diabetic retinopathy is referred to as serious non-proliferative diabetic retinopathy. The Classification of the advancement of DR within the patient is done into one of the categories: 0 - No DR , 1 – Mild, 2 – Moderate, 3 – Severe, 4 - Proliferative DR. Typically, DR is detected manually by a qualified physician by interpreting Fundus Images, which frequently leads to confusions and ultimately, prolonged therapy. Thus, we aim to provide an automated and sophisticated approach to detect DR as early as possible so that the situation can be controlled before it exacerbates. The aim is to provide an easy to use and maintainable UI to the Prediction Model in the form of a Web Application, so that users can obtain their results with minimal efforts and confusions. Hence, a complete system which enables users to upload their Fundus Images and receive results with minimal errors will be established.

2. Related Work

A summary of the existing works and research which were referred to during the implementation of this system are discussed below.

The studies [19] are conducted utilizing the database names Kaggle Diabetic Retinopathy, in which results are examined to use the average value and standard deviation of retrieved attributes. In their work, pre-processing and feature retrieval from the diabetic retinal image of fundus are performed utilizing machine learning approaches in order to diagnose diabetic retinopathy. MATLAB's DIP toolbox was used to conduct pre-processing methods like green channel separation, histogram equalization, and scaling. The images were separated into two distinct datasets, one consisting of regular stimulus images and another of retinal images altered by diabetes. From imaging data sets of normal and diabetic retinal fundus, fourteen biologically relevant characteristics are retrieved.

Seven of the most important retrieved attributes are employed for analysis, and rating these attributes is straightforward and essential to the process of distinguishing between normal and diabetic fundus images. According to the acquired data, the effusion region is the best characteristic among those that may be utilized mainly for diabetic identification, trailed by blood vessels and other attributes, indicating that effusion is one of the leading causes of DR. The characteristics included based on investigation are unique because of biological significance and documented earlier outcomes. In the future, it will be possible to derive many more aspects from attribute values like red tumors, Kapoor entropy, edema, etc. The Trainees may be utilized to classify images of DR into numerous groups depending on the importance of their characteristics, and their efficiency can be assessed using various metrics.

In this article [18], a strategy for the accurate timely identification of Diabetic Retinopathy has been devised. A cost function is used to monitor the optical disc by integrating the convergence of blood vessel and higher disc intensity attributes. In contrast to the majority of techniques that rely on active learning, we demonstrate that geometrical correlations between various attributes and tissues may be combined using primary morphological operations to produce accurate model for the studding images of retinal. Combining their tactics with a few learning methods may produce even greater outcomes.

Numerous attributes namely: blood vessels, exudates, micro aneurysms, and hemorrhages, can be identified with high precision utilizing different morphological procedures done suitably, according to the research [12]. They have developed a newer constraint for identifying the optic disc using initially they detect the important blood vessels and then using the crossover to estimate the disk's position. Overall observation of suggested model applied on the database of 516 images with multiple comparison, brightness, and illness stages reveals a rate of success of 97.1% for optic disc specificity, a sensitivity and specificity of 95.7% and 94.2% respectively for exudate identification, and a sensitivity and specificity of 95.1% and 90.5% respectively for micro aneurysm/hemorrhage identification. Among them typical serious of diabetes is DR, which causes severe vision loss or blindness. In contemporary medical science, image estimate has become a crucial tool for the accurate diagnosis of disease. Relying on retinal imaging and neural network, we have developed a computational model for predicting Diabetic Retinopathy (DR) state. Our cognitive model consists of a phase of feature extraction and a phase of classification. In the stage of extracting features, we retrieved the most pertinent features from digital fundus images by detecting Blood Vessels and Micro aneurysms.

In this study [3], the famous pertained extraction of feature method named scale invariant feature transform (SIFT) and speeded robust features (SURF) were simultaneously utilized to each retinal image in order to detect the Exudates regions. Each image Exudates are recorded in format of matrix of attributes and are utilized by SVM classifier to estimate DR. For a collection of 100 test photos, the model's average sensitivity is 94%.

Patients with diabetes [2] are urged to have periodic retinal examinations due to DR, the major reason for loss of vision among working people. Exam evaluating must be optimized due to the fact that this group is typically too huge for healthcare systems. Consequently, online service is suggested. It includes GUI for doctors, especially ophthalmologists, as well as a computerized DR programmers (using IP and different AI approaches) that reduces their effort. Total system efficiency reaches 91.9% in terms of sensitivity and 65.2% in terms of specificity.

According to study [14], DR is an eye illness creates problem to the retina and can lead to total blindness. Diabetic retinopathy must be detected early to prevent vision loss. Physical examinations, like the visual acuity test, pupil dilation, and optical coherence tomography, are utilized to diagnose DR. But, time-consuming and could damage the patients. This work use a ML system to detect the existence of DR in the human eye. The suggested approaches uses classifiers to many characteristics (e.g., optical disc diameter, lesion-specific (micro aneurysms, exudates), or the presence of hemorrhages) of a present DR database. The retrieved attributes were then utilized to make the last determination about the existence of DR. The described model made its predictions using Decision Tree, Logistic Regression, and SVM. The suggested approach yielded 88% accurate outcomes that is significantly best compared with current practices. But, described model reaches higher level in precision of 97% and recall od 92%, correspondingly, versus the current result of 72% and 63%, equating to an average improvement of more than 25% in each area, so demonstrating its immenseness.

3. System Design

During the system design of diabetic retinopathy prediction, following are the possible choices to be made.

3.1 Machine Learning

Pre-processed images will then be subjected to several Machine Learning Techniques, in order to generate an optimal model. Due to the data being in the form of images, CNNs will be of importance in generating the model, whose layer by layer breakdown will be understood during the implementation. Multiclass Classifier is generated which will classify the data among classes: 0 – No DR, 1 – Mild, 2 – Moderate, 3 – Severe, 4 – Proliferative DR. Several techniques can be employed to train the models to classify DR. Below mentioned are certain possible ones with reference to existing literature and implementations that have proven to be effective with high accuracy.

3.2 Pre-Trained Models with Fine Tuning

Several renowned model architectures exist that can be suited to be used in the project. These models have been tested and proven to be effective in area of computer vision and to add to their convenience, they come packaged with tensor flow. Certain changes such as adding or removing layers, changing weights etc can be performed to suit our purpose.

3.3 Inception_V3

Inception v3 [15] is a CNN for image processing and object detection that originated as a Google web component. It is the third version of Google's Inception CNN, which was first unveiled at the Image Net Evaluate Information. Inception v3 was meant to permit deeper networks while preventing the set of variables from becoming excessively big. Table 1 is an overview of the actual Inception v3 structure.

3.4 VGG-16

VGG16[9] is a CNN model that obtains 92.7% top ranking test performance on Image Net, a dataset including over 14 million images from 1000 classifications.

Table 1 : Inception v3 Structure

type	Patch	Input size
Conv	3X3/2	299X299X3
Conv	3X3/1	149X149X32
Convpadde	3X3/1	147X147X32
Pool	3X3/2	147X147X64
Conv	3X3/1	73X73X64
Conv	3X3/2	71X71X80
Conv	3X3/1	35X35X192
3XInceptio	As in Fig 5	35X35X288
5XInceptio	As in Fig 6	17X17X768
2XInceptio	As in Fig 7	8X8X1280
pool	8X8	8X8X2048
Linear	Logits	1X1X2048
softmax	classifier	1X1X1000

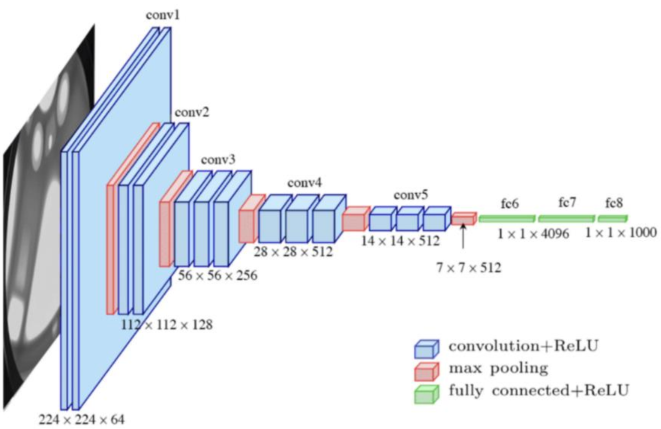

Fig. 1 : VGG 16 Structure

Figure.1 is the visual representation of the actual VGG 16 structure. Several other implementations such as ResNet50 etc. can also be used. There are several advantages like efficient Implementation, model well suited for a wide variety of purposes and proven and tested methods.

4. Proposed Methodology

The following section discusses and provides an overview on the various techniques to extract the several features available in the image data.

4.1 Data

Image Data provided by EyePacs, a channel for retinopathy displaying available on Kaggle. Indian Diabetic Retinopathy Image Dataset (IDRID) available on IEEE Data port. It includes of a significant quantity of high-resolution fundus images of the retina of both eyes that were acquired under a range of imaging settings by numerous healthcare sites using various imaging systems. Data is in the format of JPEG Images which will then have to be pre-processed so as to meet our requirements and constraints.

4.2 Image preprocessing

The database images will inadvertently contain noise which will have to be smoothed out to ensure accurate prediction of DR. Images will also have to be contrast enhanced i.e. increasing the contrast in low contrast areas and decreasing contrast in higher contrast areas. In image pre-processing, the green component is retrieved initially. Images of the retina have typically low brightness. But in the green channel, the contrast is stark. Additional pre-processing is carried out to boost the brightness of the green channel.

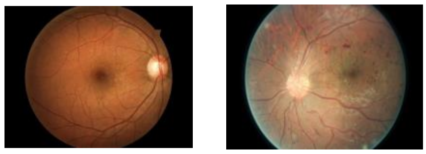

Fig. 2 : Sample Images from the Dataset

Image is divided in order to distinguish between normal and abnormal components. Several features can be obtained from the images, some of them are: Exudate Number, Exudate Area, Micro aneurysms etc. Utilizing Image Contrast to further accentuate the image's qualities, Trimming and resampling although since sizes of the original images varied greatly and some were cropped at the top and bottom, they needed to be normalized. Driven by blood vessels and other parameters, exudate area is the most useful factor for diabetic identification.

Figure 3 shows the proposed model of the system. Initially image dataset is given as input, then it goes under pre-processing stage. This step generates proposed images. These images are put under training and validation phase through trained model. Below Fig.4 gives an overview on the system design followed in this implementation. A Web Application has been implemented using NodeJS along with several packages resulting in a lightweight, modern and scalable interface to the model providing users with a seamless experience in predicting Diabetic Retinopathy classes. The MVC architecture has been followed in the implementation to provide modularity and flexibility in the development and maintenance of the application.

The following services and packages have been used to implement crucial functionalities.

(i) NodeJS:

- Express[7]: Provides necessary APIs and Middleware.
- EJS[6]: Templating Language to display dynamic content on static HTML Pages.
- Body Parse[17]: Pass data between the Views and Controllers.
- Mongoose[16]: Provides functions to communicate with MongoDB.

(ii) Cloudinary[4]: Cloud-Based Image Delivery service that provides APIs to upload images. It has several CDNs for image delivery

(iii) MongoDBAtlas[16]: Cloud-Based NoSQL data storage service.

(iv) Heroku[13]: Platform that enables deployment of applications in the cloud.

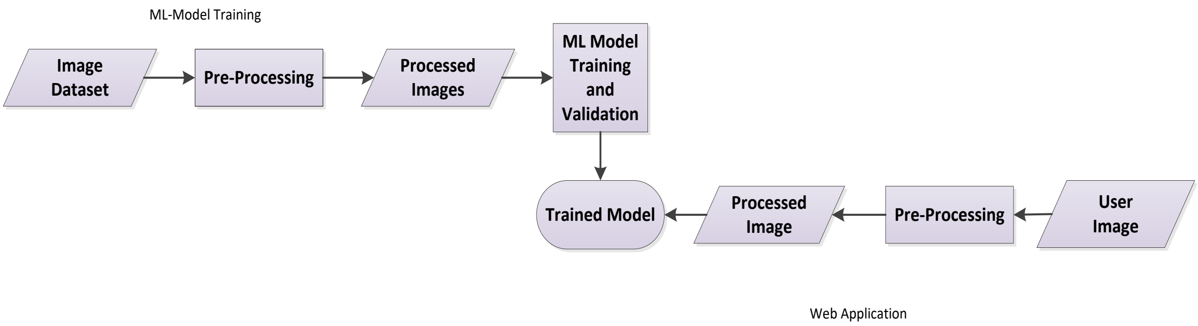

Fig. 3: Proposed Logic Flow of the System

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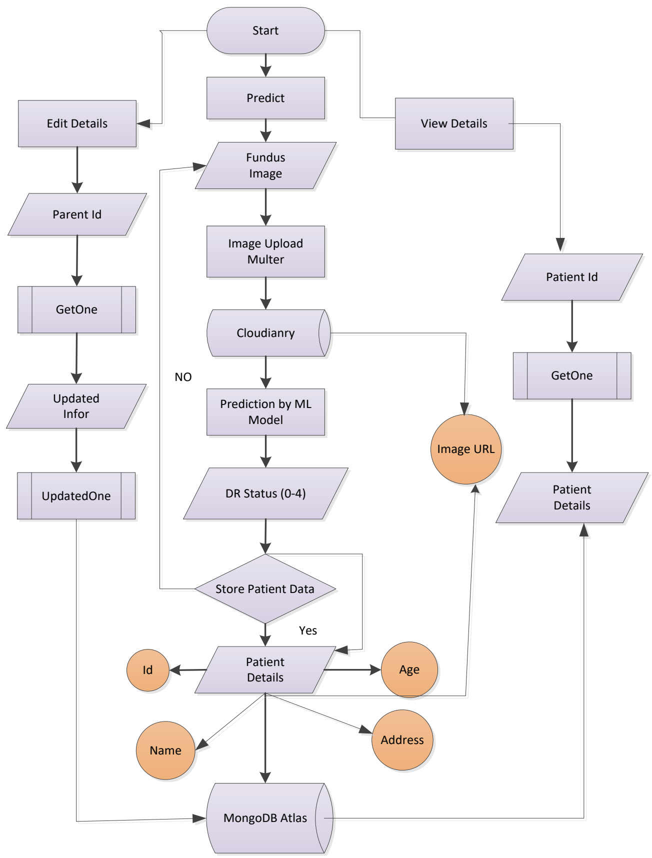

Fig. 4 : System Design Flowchart

In Figure.4 shows an additional Dark Mode functionality that has been added to improve the User Experience and Accessibility of the application. The model is run on Python rather than migrating it to JavaScript. The model was trained on cloud platforms and then saved in the H5 file format to be loaded into the deployed app. A pipeline was formulated wherein the user uploaded image would be stored in an albeit common, but secure location from which the python script would be able to extract it. Cloudinary, which is a cloud storage platform facilitates this requirement. The URL of the uploaded image is sent to the Backend by enclosing it in an HTTP Request. The Backend consists of a lightweight server developed using the Flask Framework. Gunicorn, which is a production-grade server, is used to handle the requests. The images are pre-processed once received which involves converting them into a resolution of 512 X 512, and then fed into the ML Model. The ML Model performs the prediction and generates 5 probabilities in a NumPy array corresponding to each severity class.

These probabilities are then converted into a JSON format and then sent back to the requesting application i.e. the NodeJS Frontend. Once received, the data is extracted from the JSON Object and a bar graph is generated which is used to represent the probabilities of each class(0-4). The user can now choose to either save the fundus image uploaded along with user details thereby resuming the normal flow of the application discussed in the previous sections, or they can choose to predict the severity of another input. Choosing the latter will delete the previously uploaded image from Cloudinary, following which the user will bebrought back to the image upload screen. The following components and services were used to implement the described implementation:

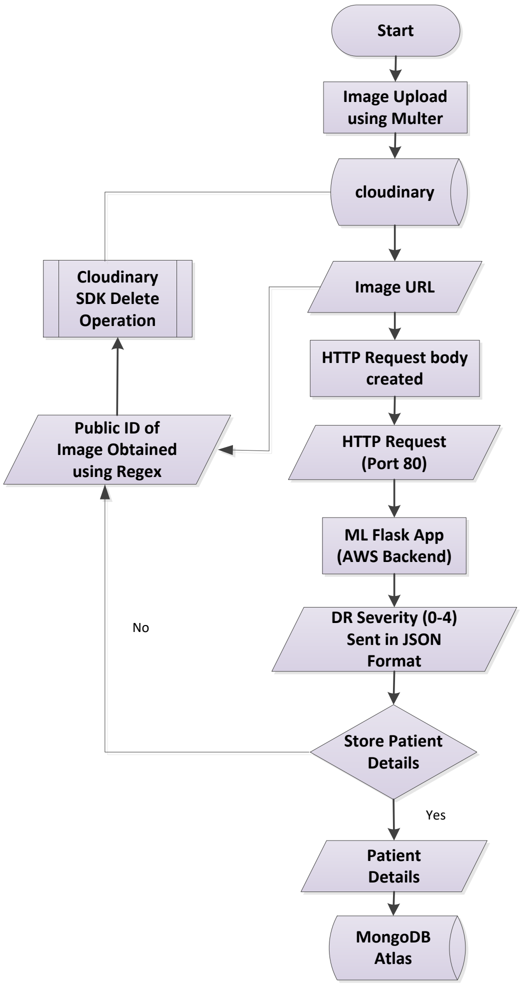

Fig. 5 : Working of the ML Backend

- Tensorflow: Contained the classes and methods needed to implement the CNN.
- Flask[8]: Framework which was used to allow the communication between the NodeJS Frontend and ML Model via HTTP Requests and API calls.
- Gunicorn[11]: Production WSGI HTTP Server used in the deployment of themodel.
- AWS: IAAS which provided a VM powerful and flexible enough to run the ML Backend.
- Systemd: Ubuntu software which allowed the ML Process to be daemonized. Thereby ensuring its state to always be running even if the server restarts.

4.1 ML Model

Dataset

The EyePACS Dataset, though large in volume, is highly skewed and noisy. Majority of the images belong to the No Diabetic Retinopathy(0 Severity) class whilst only a handful of them have DR afflicted conditions. Furthermore, some images are mislabelled, in the wrong orientation and of poor quality. To counter this, a subset of 1000 images was formed and the model was trained using this dataset. 750 images were used for training and the remaining were usedfor validation.

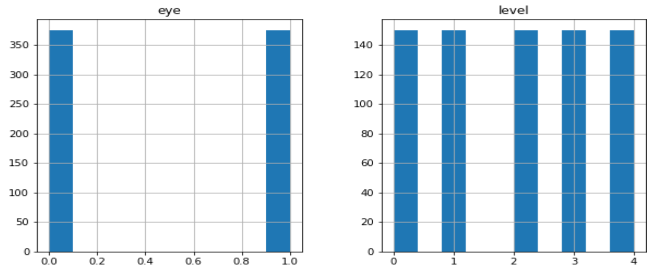

Fig. 6 : Dataset Representation

Figure.6 shows the distribution of data within the subset of the EyePACS Dataset. The subset consists of an equal distribution of Left (0) and Right (1) eyes, along with a balance across all severities.

Data Augmentation was applied to further expand the dataset so that the model can recognize images with various hues, alignments etc. (Arkhangelskiy, 2018). Below Figure. 8 shows modified Inception v3 model structure. Given the chances of more occurrences of noise in image data compared to the usual numeric ddata, this model provided exceptional results. Below Figure 7. Shows Modified Inception v3 Attention Map.

The model is successful in detecting the exudates and lesions in afflicted eyes as can be clearly seen above. Hence, this model was chosen to be implemented in the system. The model was converted into an H5 file which was then deployed onto the server.

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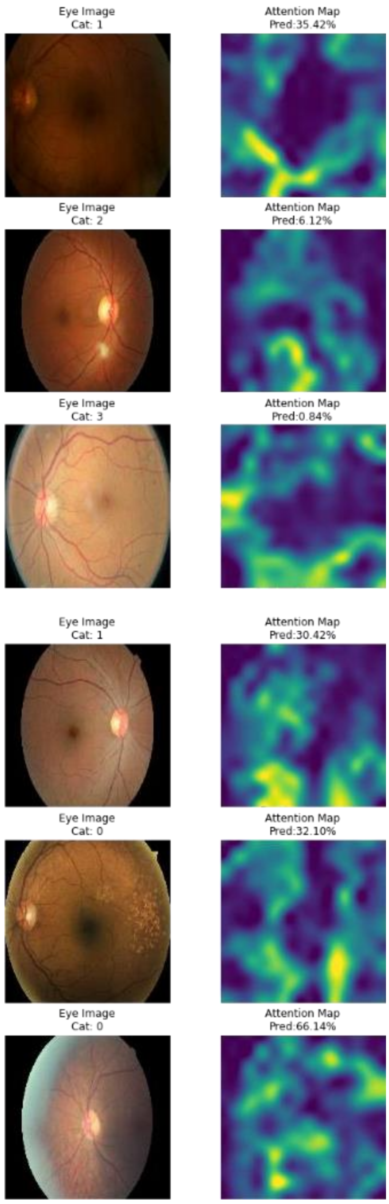

Fig. 7: Modified Inception v3 Attention Map

5. Conclusion

Hence, this implementation proves to be an efficient and accurate way to predict the severity of Diabetic Retinopathy in patients. The system can be incorporated into several environments: to reinforce the diagnosis of an ophthalmologist, to train students in the detection of DR by showing the various outcomes of predictions etc. Patient details can also be stored and retrieved at users' convenience reducing the need for repeated predictions. Implementation of such a system can also reduce the chances of misdiagnosis of a patient's condition while significantly improving the accuracy of any diagnosis made. Automatic testing methods decrease the amount of time needed to make treatments, saving ophthalmologists effort, money, and energy, which expedites the process of treating patients. Automated solutions for DR identification play a crucial role in the early diagnosis of DR. An easy to use UI ensures that there is no difficulty in operating the system, the system has been optimized in multiple ways to ensure quick results whilst keeping the minimum load on hardware.

Finally, since all the packages and dependencies involved in the development of this system are open source, the system proves to be extremely cost-effective. Sufficient care has been taken in the implementation to ensure low maintenance. In conclusion, we developed an automated, simple to use, low-cost and validated system that allows users to detect DR across multiple stages and store the relevant information for future use.

6. Future Work and Recommendations

Referring all cases of DR to ophthalmologists can overwhelm existing medical infrastructure, Recognition of mild cases DR part of medical, family physicians, and endocrinologists to take part in physician instruction and management of blood glucose, lipid levels, blood pressure, as well as other risk factors (11. Microvascular Complications and Foot Care: Standards of Medical Care in Diabetes2020, 2019). Thus, identification of moderate DR can facilitate individualized diabetic management. The current DR screening techniques are time-consuming and expensive, the implementation of such similar systems in hospitals can mitigate costs as well as chances of misdiagnosis. (Amin, 2016). Efforts can be made to improve the publicly available data, by providing better quality images as well as ensuring the correct labelling of said images. Furthermore, authorized technical institutions can arrange for the provision of the computational needs and resources so as to allow researchers to carry out experimentation and develop a model from scratch without using transfer learning from pre-trained models. Finally, attempts can also be made to use an ensemble of ML classifiers instead of the dense layers of DL models.

Conflicts Of Interest

The authors declare no conflict of interest.

Author Contributions

Conception or design of the work, Shwetha G K and Udaya Kumar Reddy ; methodology and data collection, Shwetha G K and Jayantkumar A Rathod and Sathyaprakash B P ; software, Shwetha G K,Udaya Kumar Reddy and Jayantkumar A Rathod ;analysis, Jayantkumar A Rathod and Udaya Kumar Reddy ; writing-original draft preparation, Shwetha G K, Jayantkumar A Rathod and Lolakshi P K ; critical revision of the article, Udaya Kumar Reddy ; final approval of the revision to be published , Udaya Kumar Reddy, Shwetha G K and Jayantkumar A Rathod.

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