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SIMULATION OF DIABETIC RETINOPATHY UTILIZING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT - Diabetic Retinopathy (DR) is an ophthalmic condition associated with diabetes mellitus which is caused by high blood sugar levels damaging the back of the eye (retina) via progressions inside the veins of the retina. Currently Diabetic Retinopathy is still screened as a three-stage classification which is a tedious strategy and along these lines this paper focuses on developing an improved methodology. In the present methodology, we taught a convolutional neural network form on a major dataset including around 45 depictions to mathematically analyse and characterize extreme goals i.e. hyper reflective foci **(**HRF**)** of the retina dependent on their seriousness. In this paper, DR is constructed which takes the enter parameters as HRF fundus photo of the eye. Our experimental data set is generated by processing the data provided by 301 hospitals. The experimental results show that random forest (RF) in the machine learning model can attain 80 Percentage of accuracy. Three classes of patients are considered - healthy patients, diabetics retinopathy patients and glaucoma patients. An informed convolutional neural system without a fully connected model will also separate the highlights of the fundus pixel with the help of the enactment abilities like relu and softmax and arrangement. The yield obtained from the convolutional neural network (CNN) model and the patient data achieves an institutionalized 97 percentage accuracy. The resulting methodology is therefore of great potential benefiting to ophthalmic specialists in clinical medicine in terms of diagnosing earlier the symptoms of DR and mitigating its effects.

KEYWORDS: *Diabetic retinopathy, HRF image fundus, convolutional neural network (CNN), computational medicine.*

1 INTRODUCTION

Diabetic retinopathy (DR) is an affliction arising in individuals suffering from diabetes which manifests in harm to the retina, the light-sensitive covering in the rear of the eye [1]. It is a chronic progressive disease of microvasculature associated with prolonged hyperglycaemia. Common symptoms include gradually worsening vision, sudden vision loss, shapes floating in your field of vision, blurred or patchy vision and eye pain or redness. DR is therefore a genuine sight-threatening ailment associated with diabetes. The capacity of the body to store and utilize sugar is mediated by methods for diabetes. The confusion to the body is associated by utilizing overabundance of sugar degrees inside the blood which can damage the eyes. Over a timespan, diabetes can seriously inhibit venous function in the retina. Diabetic retinopathy is a circumstance that happens while blood and various liquids start spilling from smaller veins exacting the retinal tissue to expand. This results in overcast or obscured vision. This condition normally impacts both eyes. The longer an individual has diabetes the greater the likelihood that diabetic retinopathy may develop. Diabetic people, who suffer long interims of high glucose, will experience unbalanced fluid collection in the focal point which accordingly modifies the focal point, prompting obscured vision. In any case, when glucose degrees are underneath control, opthalmic functions will improve. The early degrees of diabetic retinopathy do not exhibit any noticeable indications [2]. To mitigate the onset of DR, diabetic patients therefore require continuous eye assessment. Identifying and treating the disease at a development level can successfully limit the negative impacts of diabetic retinopathy [3-5]. Laser treatment has emerged as a major tool for combatting DR symptoms [6]. Also known as laser photocoagulation**,** this procedure generates minute, painless retinal burns which seal off leaking vessels and reduce swelling in the eye [7]. Other surgical procedures may also be required to seal the spilling veins or to prevent other veins from spilling and may further necessitate infusion prescriptions for the eye. Individuals with extreme diabetic retinopathy may require also need surgery to evacuate and supplant the gel-like liquid in the rear of the eye (vitreous humour) [8]. Surgeries may likewise be expected to fix a retinal separation. Retinal separation is a partition of the light-getting reaching the rear of the eye. Patients can help forestall or slow the development of diabetic retinopathy by taking endorsed prescription, adhering to controlled eating routine, conducting eye exercised, controlling hypertension and abstention from alcohol and tobacco smoking. Diabetic retinopathy is usually diagnosed entirely by recognizing abnormalities on retinal images taken by a photographic procedure known as fundoscopy. Color fundus photography is deployed principally for staging the disease. Fluorescein angiography is used to assess the extent of retinopathy which is critical in assisting a treatment plan development. Optical coherence tomography (OCT) is used to determine the severity of edema and treatment response [9]. Since fundoscopic images are the main sources for diagnosis of diabetic retinopathy, *manually analyzing those images* can be time-consuming and unreliable since there is considerable inconsistency and variability in detecting abnormalities with time. Therefore, biomedical engineers and scientists have pursued computer-aided diagnosis approaches [10] to automate the process. This involves extracting information about the blood vessels and any abnormal patterns from the rest of the fundoscopic image and analyzing them to make more robust clinical decisions for the benefit of the patient. In computer modelling, a powerful modern technique has been neural networks [11, 12]. The *convolution neural network* (CNN) is a subset of a profound learning neural system. It is fundamentally utilized for picture order and picture investigation. The objective behind CNN is to imitate how the human mind breaks down a picture.

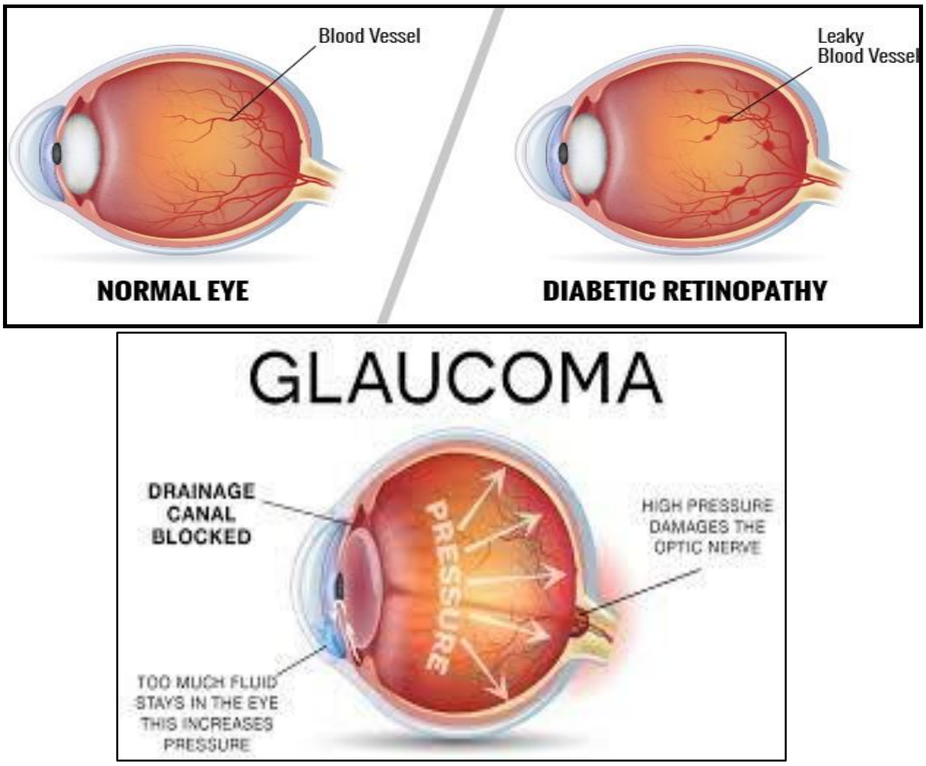


Fig. 1 Comparison of healthy, diabetic retinopathy and glaucoma-afflicted human eye

https://plessenophthalmology.com/diabetic-retinopathy/

http://pgheyemds.com/glaucoma-evaluation-and-treatment/

Figure 1 shows the contrast between the normal healthy human eye, a diseased diabetic eye and glaucoma-afflicted eye including the principal locations of degeneration. Many interesting studies of computational analysis of DR have been communicated in recent years. Deep learning is a newer and more advanced subfield in artificial intelligence (AI). Various types of classifiers based on machine-learning methods have been proposed and applied to classify the different regions of interest from a set of extracted features and these include support vector machines, artificial neural networks, K-nearest neighbours, lattice neural networks, Gaussian mixture models etc. However deep-*learning classifiers* such as convolutional neural networks have the advantage that they avoid the extraction of handcrafted features. They are known as *supervised learning* and yield improved results since they employ classifiers to categorize image pixels associated with either retinal vessels or background (non-vessel). Extensive details of sensitivity, specificity, and area under curve (AUC) for both internal and external validation sets for any DR detection, prompt referral, and STDR were computed and showed excellent potential of CNN in DR diagnosis.

The motivation of the paper is to create a deep Convolutional Neural Network for the classification of Diabetic Retinopathy. This method is varying from existing model which uses Convolutional Neural Network without any fully connected layer which reduces computational complexity and increases its efficiency. Apply the Transformation learning to features and class is identified from image data sets. The experimental results have demonstrated to achieve the better accuracy.

The aim of our study is to validate a machine-based algorithm developed based on deep convolutional neural networks (CNNs) as a tool for screening to detect referable diabetic retinopathy (DR). As such this approach mitigates the need for the program to perform a specific task and instead recognizes the patterns and learns to predict automatically. CNN is able to access neural networks and mimic the human brain in decision-making processes but requires very large database for training. The deep neural network features convolutional layers and pooling layers. It aims essentially to produce a more cost-effective, accessible and accurate imaging methodology for identifying DR symptoms and mitigating deterioration in vision and curbing patient blindness. Details are provided therefore as to how the convolutional neural network form is taught on a major dataset including around 45 depictions to mathematically analyse and characterize extreme goals i.e. hyper reflective foci (HRF) of the retina, dependent on their seriousness. DR is constructed which takes the enter parameters as HRF fundus photo of the eye. An informed convolutional neural system without a fully connected model is shown to be able to successfully separate the highlights of the fundus pix with the help of the enactment abilities like relu and softmax and arrangement. The yield obtained from the convolutional neural network (CNN) model and the patient data achieves an institutionalized 97 percentage accuracy. The results could potentially revolutionize tele-screening in ophthalmology, especially where people do not have access to specialized health care and ultimately improve the quality of eye health globally.

The major contribution of this study are as follows:

- In this paper diabetics retinopathy is classified into three processes by using deep learning.
- At first find the affected eyes disease diabetics' retinopathy by using deep learning based on convolutional neural network to develop classify the disease by using High resolution funds images database of the patients classifications are Healthy patients, Diabetics retinopathy patients, Glaucoma patients.
- Early detection of this condition is critical for good treatment. We will demonstrate the use of Convolutional Neural Networks (CNN) on images of infected retina for the recognition task of DR staging. With the help of deep learning we can detect DR at its initial stage.
- Convolutional Neural Network without any fully connected layer which reduces the computational complex and also increase its efficiency. Hence treatment can be perused earlier with help of doctors because of taken short time to diagnosis disease.

- This research work focused on informed convolutional neural system without a fully connected model will also separate the highlights of the fundus pix with the help of the enactment abilities like relu and softmax and arrangement. The yield obtained from the convolutional neural network (CNN) model and the patient data achieves an institutionalized 97 percentage accuracy. Convolute eye diseases with significant contribution in the field. In this manuscript authors are used convolution neural network methods.

The organization of the paper as follows. Section 2 provides related work. Section 3 presents a description of methods for image processing techniques. Section 4 gives the dataset description. Section 5 introduces the proposed methodology. Section 6 provides implementation details. Results and discussion are given in section 7. Conclusions are given in section 8.

2. RELATED WORK:

Many interesting studies of computational analysis of DR have been communicated in recent years. Xu *et al.* [13] developed algorithms featuring fractal models to simulate the main structure of neovascularization (NV) and an adaptive color generation method to assign photorealistic pixel values to the structure to visualize how DR enters a vision-threatening phase. Khomri *et al.* [14] used computer-aided diagnosis (CAD) systems to visualize retinal vessel segmentation in diabetic retinopathy to assist ophthalmic surgeons in detecting vessels of varying diameters in high- and low-resolution fundus images. Many other computational approaches have been implemented in DR studies. These include Chutatape *et al.* [15] Gaussian and Kalman filters), Cinsdikici and Aydın [16] (mf/ant (matched filter/ant colony) algorithms), Hassanien et al. [17] (bee colony swarm optimization and fuzzy logic techniques), Haddouche *et al.* [18] (Markov random field digital models), Annunziata *et al.* [19] (multiscale Hessian-based enhancement bioinformatic algorithms), Miri and Mahloojifar [20] (curvelet transform and multistructure morphology coding for retinal image reconstruction), Al-Rawi and Karajeh [21] (genetic algorithm matched filter optimization), Larsen *et al.* [22] (automated detection techniques). Good perspectives of studies have been summarized in Osareh *et al.* [23], Usher *et al.* [24] and also Mookiah *et al.* [25].

Deep learning is a newer and more advanced subfield in artificial intelligence (AI). Various types of classifiers based on machine-learning methods have been proposed and applied to classify the different regions of interest from a set of extracted features and these include support vector machines, artificial neural networks, K-nearest neighbors, lattice neural networks, Gaussian mixture models etc. However deep-*learning classifiers* such as convolutional neural networks have the advantage that they avoid the extraction of handcrafted features. They are known as *supervised learning* and yield improved results since they employ classifiers to categorize image pixels associated with either retinal vessels or background (non-vessel). An excellent early study of neural networks in DR was presented by Gardner *et al.* [26]. Wan *et al.* [27] quite recently conducted a seminal investigation in automatic classification of DR fundus images using convolutional neural networks (CNNs) for enhanced in which they employed transfer learning and hyper-parameter tuning in AlexNet, VggNet, GoogleNet, ResNet platforms and furthermore applied the Kaggle platform for training these models. They achieved a 95.68% classification accuracy confirming superior performance of CNNs and transfer learning in ophthalmic DR image classification. Further corroboration of CNN efficiency in DR imaging has been provided by Roth *et al.* [28] and Prentašić and Lončarić [29]. An excellent recent clinical screening study has been presented by Shah *et al.* [30]. They reported on extensive trials at Sankara Eye Hospital, Bengaluru, Karnataka, India, in which a CNN algorithm for detecting DR was validated at using an internal dataset consisting of 1,533 macula-centered fundus images collected retrospectively and an external validation set using Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology (MESSIDOR) dataset. Extensive details of sensitivity, specificity, and area under curve (AUC) for both internal and external validation sets for any DR detection, prompt referral, and STDR were computed and showed excellent potential of CNN in DR diagnosis.

Author name	**Paper title**	**Year**	**Contribution of work**	**Advantage**	**Disadvantage**
Simonyan K and Zisserman	Very Deep Convolutional Networks for Large-Scale Image Recognition	2014	ConvNet(convolutional neural network), ImageNet (image database)	The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision	Performance at the pixel level is poor by using mobile photography It does not rely on expert knowledge or manual segmentation for detecting relevant patterns
Kaiming He, Xiangyu Zhang Shaoqing Ren Jian Sun	Deep Residual Learning For Image Recognition	2016	ImageNet (image database), CIFAR-10(Canadian institute for advanced research), ILSVRC (ImageNet large scale visual recognition), COCO (common object)	The image segmentation is process is easy and pixel of image is good	Complexity more by using Imagenet residual nets 3.57% error occurs
Otálora S, Perdom O,González F., and Müller H	Training Deep Convolutional Neural Networks with Active Learning for Exudate Classification In Eye Fundus Images	2017	SGD (stochastic gradient descent)	By using deep learning to identify large dataset and its take short time and hence treatment can be perused earlier in stage.	CNN for recursive in medical tasks is often difficult due to the lack of data sample loss in automatic detection tool to support the grading of diabetic retinopathy and macular edema.
Adem K	Exudate Detection For Diabetic Retinopathy With Circular	2018	DICOM (digitial imaging and	It is not fully connected layer so required of time taken too soon.	Small dataset can be used Image segmentation

	Hough Transformation And Convolutional Neural Networks		communications), CUDA (compute unified device architecture)		process taken more time
Sangeethaa SN and Maheswari PU	An Intelligent Model for Blood Vessel Segmentation in Diagnosing DR Using CNN	2018	GPU (graphical processing unit), CNN (convolutional neural network)	CNN Performs Multiple Convolutions on an input and classification layer networks.	It contains smaller database, images are taken into GPU
Khan etal	A review of retinal blood vessels extraction techniques: challenges, taxonomy, and future trends	2019	This survey presents a comprehensive review of such techniques, strategies, and algorithms presented to date. The techniques are classified into logical groups based on the underlying methodology employed for retinal vessel extraction.	This survey presents a valuable resource for researchers working toward automatic extraction of retinal vessels. We have classified the retinal vessels segmentation approaches into more logical groups for ease readers.	This poor contrast is satisfactory for specific considerations like fractal dimension or tortuosity and computing the vessel width usually needs greater resolution photographs to attain superior accuracy.
Jyotiprava Dash NilamaniBhoi	A thresholding based technique to extract retinal blood vessels from fundus images	2017	Many thresholding technique have been proposed for segmenting retinal images but we have used here the local adaptive thresholding for segmenting retinal blood vessels as it can gives better segmentation performance with a lower execution time as compared to other conventional thresholding approaches.		A post-processing phase is carried out in order to obtain a final segmented image.
Juso et al	An overview of retinal blood vessels segmentation	2016	This paper provides a review on retinal vessel segmentation. Vessel segmentation is completed before further image analysis to detect any retinal abnormalities. Therefore, developing an efficient and fast	Vessel segmentation must be completed accurately to obtain good results for further image analysis.	Future work should focus on improving the literature review regarding the details of the methods used in vessel segmentation and further analysis of retina vessels,

			algorithm that can achieve a high level of accuracy is important.		such as changes in diameter, bifurcation angles, and tortuosity, should be included.
Jasem Almotiri et al.	Retinal Vessels Segmentation Techniques and Algorithms: A Survey	2018	The accurate detection and segmentation of the retinal vascular structure forms the backbone of a variety of automated computer aided systems for screening and diagnosis of ophthalmologic and cardiovascular diseases. Even though many promising methodologies have been developed and implemented, there is still room for research improvement in blood vessel segmentation methodologies, especially for noisy and pathological retinal images outside the limited number of retinal images available in public datasets.	The purpose of this paper is to provide a comprehensive overview for retinal vessels segmentation techniques. These methodologies were evaluated using publicly available datasets. Various retinal vessels segmentation methodologies follow similar procedures: each methodology initiates by pre-processing step, where the green layer (or grey) is extracted from the raw color retinal image, and then the contrast of the image is enhanced.	In real-life applications, retinal vessels segmentation systems will not replace the experts' role in diagnosis; rather, they will enhance the diagnosis accuracy and reduce the workload of the ophthalmologists. Therefore, large volume of patients' images can be processed with high diagnosis accuracy and comparable time.
lShaohua Wan etal[a]	Deep convolutional neural networks for diabetic retinopathy detection by image classification	2018	Convolutional Neural Networks for detecting Diabetic Retinopathy and transfer learning are presented to classify Diabetic Retinopathy fundus images and automatic feature learning reduces the process of extracting the feature of fundus images to attempt towards.	We employ publicly available Kaggle platform for training these models. The best classification accuracy is 95.68% and the results have demonstrated the better accuracy of CNNs and transfer learning on DR image classification	It concentrates on the classification.

Toufique ahmed soomro etal	Deep Learning Models for Retinal Blood Vessels Segmentation: A Review	2019	With the advances in image processing and artificial intelligence, computer vision-based techniques have been applied rapidly and widely in the field of medical images analysis and are becoming a better way to advance ophthalmology in practice.	We focus on recent advances in deep learning methods for retinal image analysis.	This paper foresees the future direction of how the new technology will help limit vision loss, improving the early diagnosis accuracy for effective treatments and thereby significantly improve the life quality of patients with eye diseases. This paper explores and identifies a flexible and reliable computerized system that can automatically identify the change in the blood vessels and predict the potential disease as early as possible.

3. METHODS

An AI algorithm to detect DR was validated at our hospital using an internal dataset consisting of 1,533 macula-centered fundus images collected retrospectively and an external validation set using Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology (MESSIDOR) dataset. Images were graded by two retina specialists as any DR, prompt referral (moderate non-proliferating diabetic retinopathy (NPDR) or above or presence of macular edema) and sight-threatening DR/STDR (severe NPDR or above) and compared with AI results. Sensitivity, specificity, and area under curve (AUC) for both internal and external validation sets for any DR detection, prompt referral, and STDR were calculated. Inter observer agreement using kappa value was calculated for both the sets and two out of three agreements for DR grading was considered as *ground truth* to compare with AI results. It is important to briefly review previous frameworks which have endeavoured to arrange whether the subject is influenced by Diabetics Retinopathy sickness. Every method has its own focal points and restrictions.

(i)*Very Deep Convolutional Networks for Large-Scale Image Recognition* -this examines the impact of the convolution arrange profundity on its exactness in the huge scale picture acknowledgment setting. Our principle commitment is an intensive assessment of systems of expanding profundity utilizing a design with little (3 × 3) convolution channels, which shows that a critical enhancement for the earlier workmanship setups can be accomplished by pushing the profundity to 16–19 weight layers. These discoveries were the premise of our Image Net Challenge 2014 accommodation, where our group verified the first and the second places in the limitation and order tracks individually.

(ii)*Deep Residual Learning for Image Recognition neural systems* – these are progressively hard to prepare. We present a lingering learning system to facilitate the preparation of systems that are considerably more profound than those utilized beforehand. On the Image Net dataset, we assess remaining nets with a profundity of up to 152 layers which is 8× more profound than VGG nets [40] yet at the same time having lower multifaceted nature. An outfit of these lingering nets accomplishes 3.57% mistake on the Image Net test set. This outcome won the first spot on the ILSVRC 2015 order task. We likewise present investigations on CIFAR-10 with 100 and 1000 layers. The profundity of portrayals is of focal significance for some, visual acknowledgment undertakings. COCO objects location dataset. Profound leftover nets are establishments of our entries to ILSVRC and COCO 2015 rivalries, where we additionally won the first places on the errands of Image Net location, Image Net restriction, COCO recognition, and COCO division.

(iii)*Training Deep Convolutional Neural Networks with Active Learning for Exudate Classification in Eye Fundus Training* – this is a profound convolutional neural system for arrangement in restorative assignments and is regularly troublesome owing to the absence of clarified information tests. Profound convolutional systems (CNN) have been effectively utilized as a programmed recognition apparatus to help the reviewing of diabetic retinopathy and macular edema. The CNN model utilizes the *normal angle length*, a functioning learning calculation to choose the most useful fixes and pictures, joining prior and to a superior neighbourhood and is more ideal than the typical SGD (Stochastic Gradient Descent) technique. Our technique additionally creates valuable covers for forecast and fragments districts of intrigue.

(iv)*Exudates Detection for Diabetic Retinopathy with Circular Hough Transformation and Convolutional Neural Networks* -the wavelet highlights are utilized for pneumonia discovery and the proposed equal strategy improves the registering speed on more than 12.75 occasions; it is as yet an open issue since digitization of this procedure incurs high computational expenses.

(v)*An Intelligent Model for Blood Vessel Segmentation in Diagnosing DR Using CNN* - diabetic retinopathy (DR) is an eye malady, which influences individuals who are for the most part having diabetes for over 10 years. The ophthalmologist distinguishes when the expanded eye test causes extreme in any of the accompanying deviations in the retina: changes in veins, spilling veins, recently developed veins, growing of the macula, changes in the focal point, and harms to the nerve tissue. It can in the long run lead to vision misfortune.

The early discovery of DR forestalls the reason for visual deficiency. The current work uses the retinal picture division and extraction of veins by morphological handling, thresholding, edge location, and versatile histogram levelling. For the programmed finding of DR from the fundus picture, we built up a system with CNN design by using graphical processor unit (GPU). We prepared this system on the openly accessible dataset, for example, DRIVE, DIARETDB0, and DIARETDB1_v1, and the pictures gathered from the *Aravind Eye Hospital, Coimbatore, India*. Our proposed CNN accomplishes an affectability of 96%, a particularity of 93%, and a precision of 92.9% containing a database of 854 pictures. The study of taking care of clinical issues by investigating pictures produced in clinical practice is known as *restorative picture examination*. The point is to remove data in a successful and proficient way for improved clinical diagnoses. Specialists have characterized [31] that DR is a leading contributor to visual impairment in America and over 99% of cases in India. India and China presently represent more than ninety million diabetic patients. This constitutes an extraordinarily wide assortment of people suffering from visual impairment until and unless diabetic retinopathy might be identified early. The programmed diabetic retinopathy treatment therefore seriously needs modernizing to more robustly and quickly and indeed much earlier in diagnosis, in order to identify indicators of retinopathy, alongside haemorrhages and exudates, in retinal tinge fundus pictures.

4. DATASET DESCRIPTION

This stage is executed in two basic parts- *test data* and *preparing data* that the neural system can accommodate. The pictures are taken from HRF, in which each image is a compressed record. The photographs have been comparably arranged in explicit degrees of Healthy individual, Glaucoma and Diabetic retinopathy for the neural network. Table 1 gives the training dataset and test dataset.

Table 1: Training dataset and test dataset.

Image	Dataset
Train Dataset	45
Test Dataset	15

In the below figure there might be an image containing the photo call and level. It demonstrates that the photograph has a place with which level of diabetic retinopathy the python programming orders photograph.Fig.2 shows the HRF Funds Image of training datasets and Fig.3 shows the HRF Fundus Image of tested dataset.

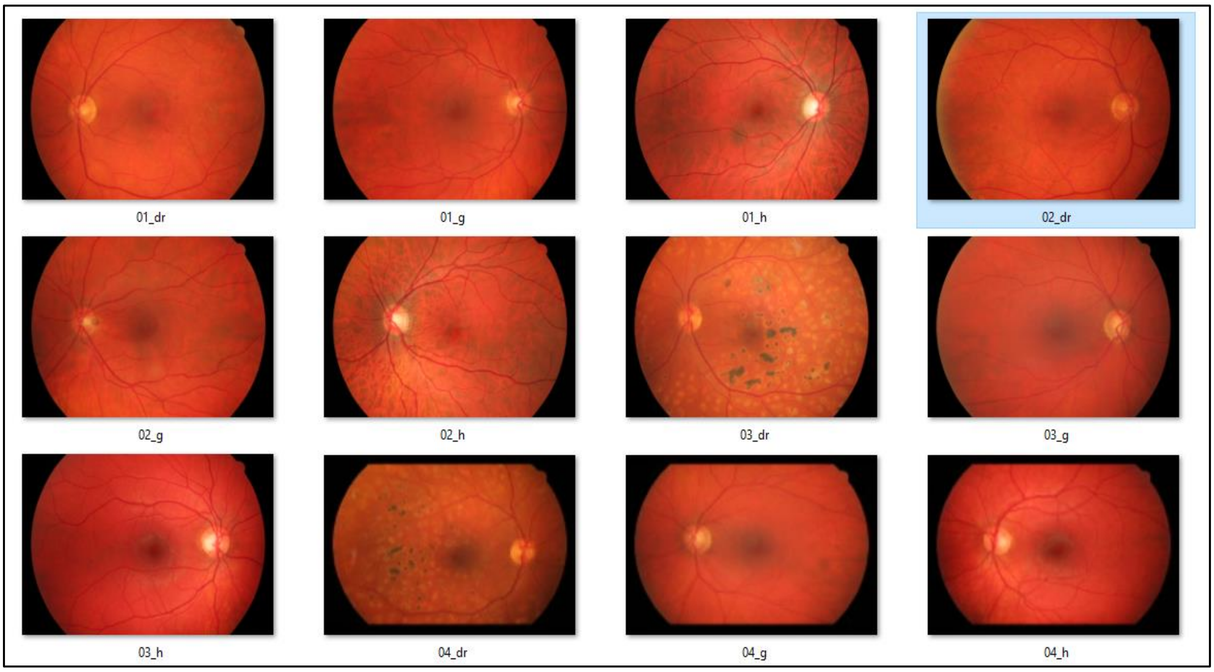


Fig-2: HRF Fundus Image of training datasets

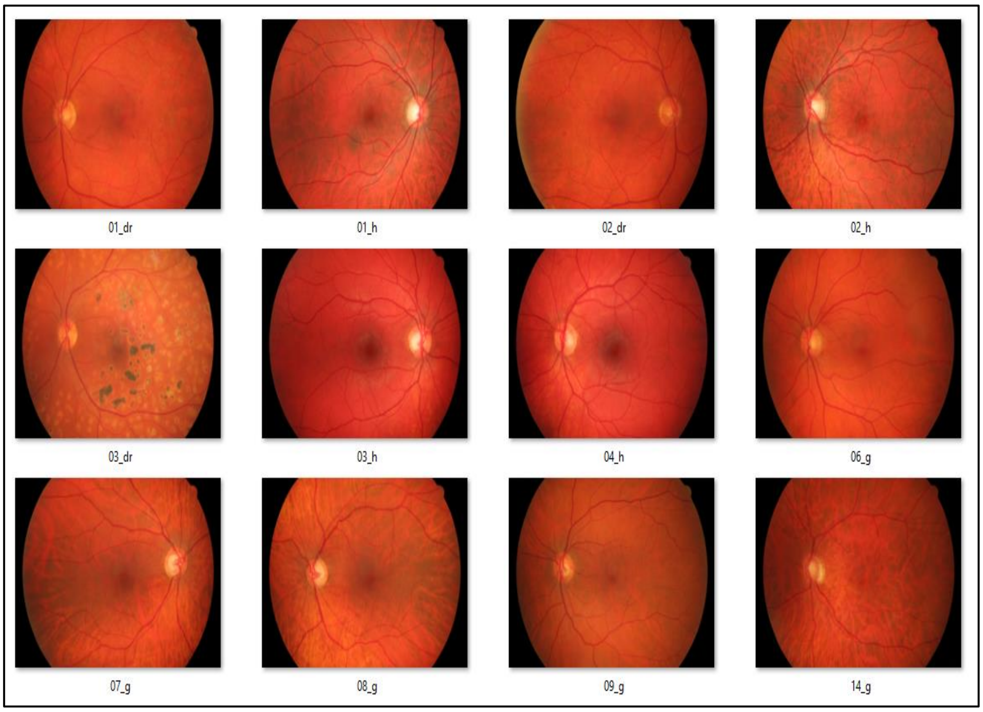


Fig-3: HRF Fundus Image of tested dataset.

Image resizes: all the assets pictures taken for preparing have 584*876*three goals yet could be resized directly down to 1*3 goals. Python's opencv2 library has been utilized to resize the photograph, setting the outstanding parameter as 97%. Fig .4 shows the HRF Fundus Image of Diabetic Retinopathy

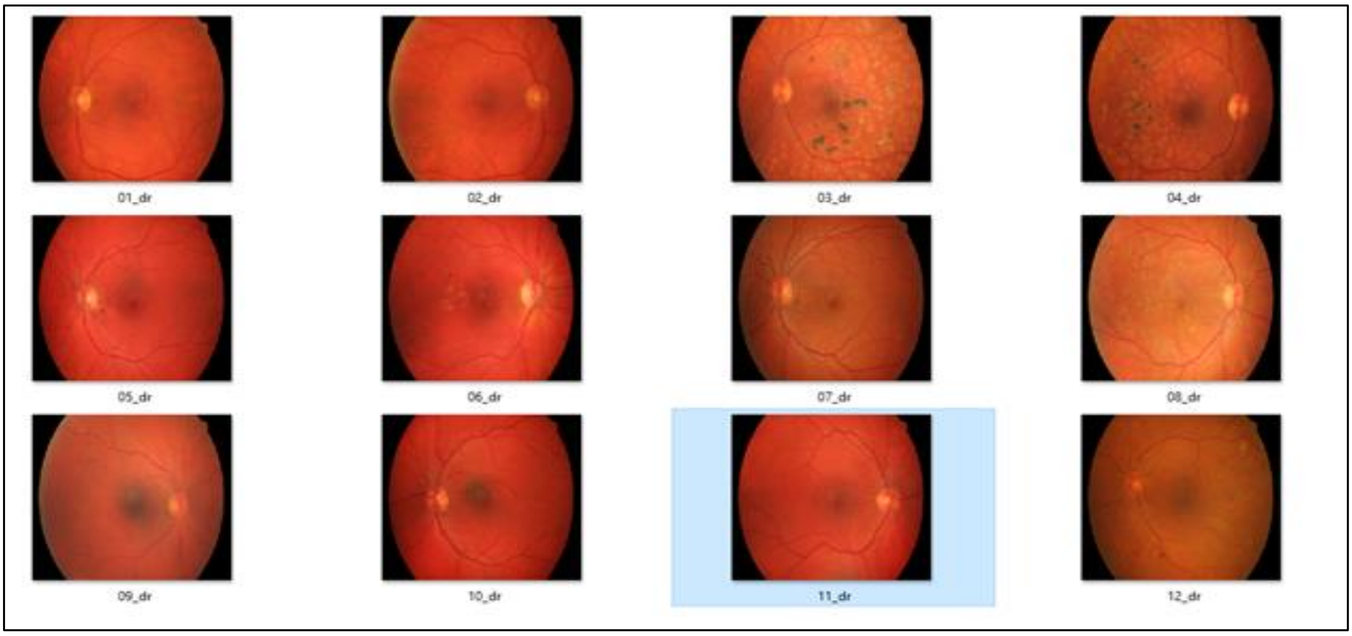


Fig-4: HRF Fundus Image of Diabetic Retinopathy.

The next image Fig. 5 shows the fundus photo of the healthy human eye. This photo is additionally prepared to test whether it actually qualifies as a fundus photo or not. The proposed framework works as a web application where the client can include any kind of picture and can trick the neural system. Thus, to avoid this dilemma, a “get out” must be applied that will best allow the fundus picture to be outperformed by the neural system (over-ridden).

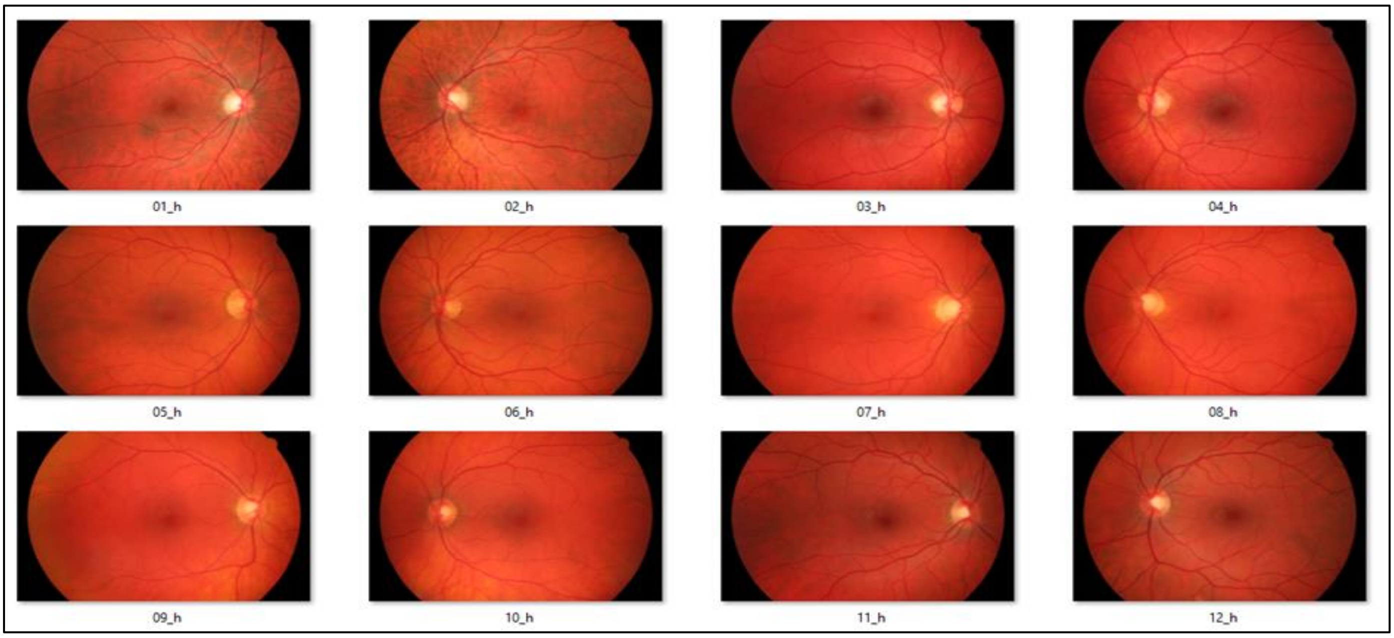


Fig-5: **HRF Fundus picture of healthy human eye**

Glaucoma is an abnormal eye condition in which the aqueous humour (fluid at the front of the eye) reaches a higher than normal inter-ocular pressure. If untreated, it can seriously damage the optic nerve, causing a loss of vision or possibly visual impairment. Glaucoma is routinely called "the sneak cheat of sight." Often, by the time the patient becomes aware of the condition, glaucoma must be ended, not merely controlled or turned around. The next image shows a human eye with glaucoma. Fig.6 shows the HRF Image fundus of Glaucoma.

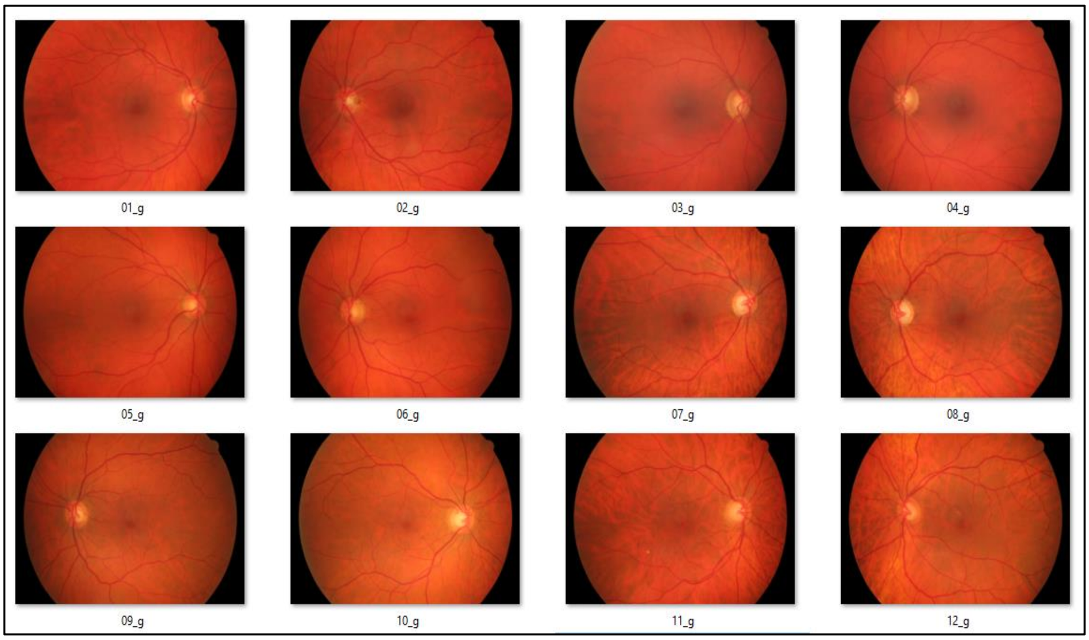


Fig-6: HRF Image fundus of Glaucoma

The channel fundamentally utilizes opencv2 python library which employs a Scale-Invariant Feature Transform (SIFT) calculation to evaluate the key components and the key point depiction of the picture. Key point descriptor is a 15*15 framework that portrays the network around the key factor. On affirmation, that the picture is a HRF fundus picture it is then passed to the neural system. The design of the neural system is elaborated in due course.

5. PROPOSED METHODOLOGY:

Convolutional Neural Systems

In deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep neural networks, most commonly applied for analyzing visual imagery. CNNs use relatively little pre-processing compared to other image classification algorithms. Criteria that make a model desirable include *robustness or stability, scalability, simplicity, speed, portability, adaptability (to changes in the data), and accuracy*. **Fig. 7** shows the logical flowchart for CNN study which is employed in the CNN design used in the current investigation.

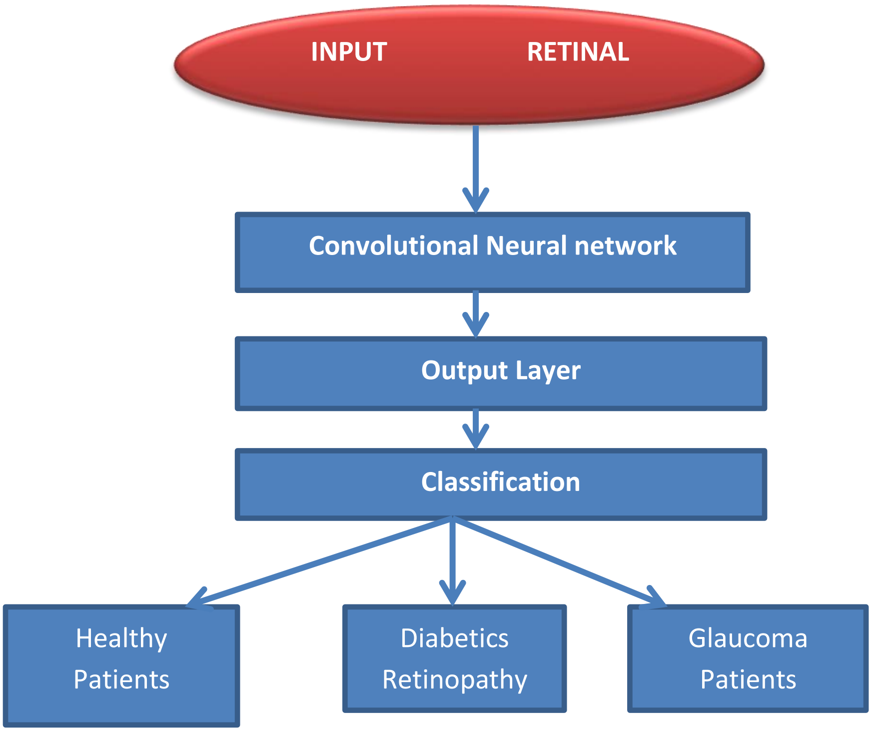


Fig. 7: Logic flowchart for CNN study

The convolutional neural system, or CNN (see **Fig. 8**) for short, is a specific kind of neural network model intended for running with two-dimensional picture measurements, despite the fact that they can be utilized with one-dimensional and three-dimensional data. Fig.8 shows the Convolutional neural network architecture.

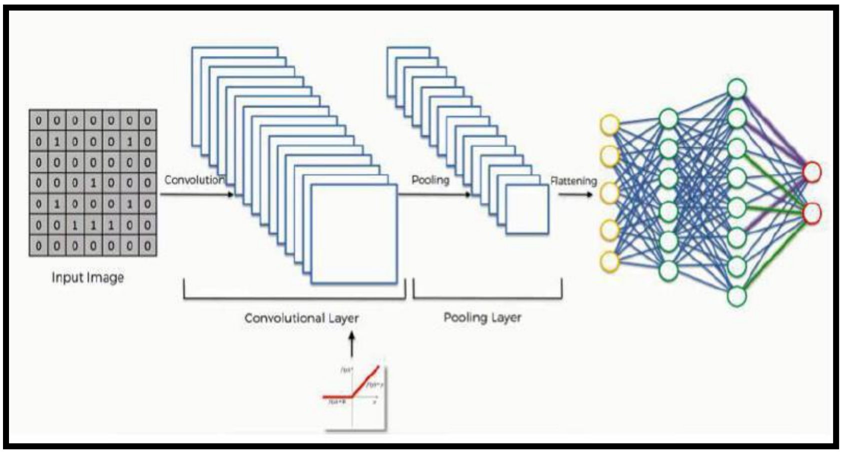


Fig-8: Convolutional Neural Network Architecture

Vital to the convolutional neural system is the *convolutional layer* that gives the network its name. This layer plays out an activity called a "convolution". Convolution is a straight activity that incorporates the augmentation of a lot of loads with the center, much like a conventional neural network. Given this the methodology becomes intended for two-dimensional information, the increase is practiced between a variety of enter insights and a two-dimensional cluster of loads, known as a channel out or a piece. Convolution Neural Systems are much the same as ordinary Neural Systems in that they can be composed of neurons which have learnable loads and inclinations. Every neuron gets a few data sources, plays a dab item and alternatively tails it with a non-linearity. The total network despite everything communicates a *solitary differentiable rating capacity*: from the crude picture pixels on one quit to class rankings on the other. Additionally, they also feature a misfortune work (e.g. SVM/Softmax) at the last (without completely associated) layer and every one of the tips/insights which were created in the current study are based on learning in conventional Neural Systems. The straightening layer changes over the 1*3 framework of picture into one unmarried measurement exhibit which enters the thick layer. During the operation of a neural network, the enter portrayal is leveled into a *capacity vector* and passed through a network of neurons to anticipate the yield probabilities. The accompanying picture portrays the pulling down activity. The columns are linked to shape a *long trademark vector*. In the event, that *more than one information layer* is available, its columns are additionally linked to frame a reasonable longer trademark vector. The capacity vector then proceeds through more than one thick layer. At each thick layer, the component vector is duplicated by utilizing the layer's loads, with its biases, and passed via a non-linearity. Further noteworthy data underneath will be elaborated upon; any way a basic Conv Net for CIFAR-10 characterization will have the design [INPUT - CONV - RELU - POOL - CLASSIFICATION] subtleties. With regards to a convolutional neural network, the following notation is of relevance:

Input [584*876*x3] will hold the *uncooked pixel estimations* of the photo, right now photograph of width 32, tallness 32, and with three tinge channels **R, G, B**.

CONV layer will process the yield of neurons which can be identified with neighbourhood areas inside the info, each registering a spot item among their loads and a little district which they are connected to in the information degree. This may achieve degrees which incorporate [190*288*8] on the off chance that we resolved to apply 8 filters.

RELU layer will apply an element-wise initiation together with the max(0, x) thresholding at zero. This leaves the size of the amount unaltered ([95*144*8]).

MAX POOL layer will execute a down sampling activity along the spatial measurements (width, top), bringing about amount incorporating [8*14*64] and degree of size [1x3], where every one of the ten numbers compare to a class score, together with some of the 10 classes of CIFAR-10. Similarly, as with ordinary Neural Systems and as the call infers, each neuron on this layer can be connected to the entirety of the numbers inside the past volume.

CLASSIFICATION layer provides results for healthy eye patients, glaucoma patients *or* diabetic retinopathy (DR) patients 1*3.

Therefore, the CNN machine learning code changes the first picture layer by the method of layers from that of a pixel esteem to the last class scores. Note that a few layers incorporate parameters. Specifically, the CONV layers perform changes which are an attribute of not easily accessible initiations inside the info Degree, yet additionally of the parameters (the loads and inclinations of the neurons). On the contrary, the RELU/POOL layers will uphold a fixed trademark. The parameters inside the CONV layers will be prepared with slope plunge so the class rankings of the ConvNet processes are reliable with the marks in the tutoring set for each image. Table 2 shows the Convolutional neural network architecture which is given below.

Table 2 Convolutional Neural Network Architecture.

Layer name	Kernel Size	No of Kernels	Stride	Image size
Image Input Layer	-	-	-	584x876x3
Conv layer 1	15x15	8	3x3	190x288x8
Relu	-	-	-	-
Max pooling 1	2x2	-	2x2	95x144x8
Conv layer 2	7x7	16	1x1	89x138x16
Relu	-		-	89x138x16
Max pooling 2	2x2		2x2	44x69x16
Conv layer 3	5x5	32	1x1	40x65x32

Table 2 Convolutional Neural Network Architecture (ctd)

Relu	-		-	40x65x32
Conv layer 4	3x3	32	1x1	38x63x32
Relu	-		-	38x63x32
Maxpooling 3	2x2		2x2	19x31x32
Conv layer 5	3x3	64	1x1	17x29x64
Relu	-		-	17x29x64
Max pooling 4	2x2	-	2x2	8x14x64
Conv layer 6	1x1	3	1x1	1x1x3
Softmax Layer	1x1x3	-		1x1x3
Flatten	1x3	-		1x3
Classification Layer	3	-		-

5.1 Convolutional Layer

The main layer is the convolutional layer, which executes overwhelming calculations which make further action simple. This layer functions as an info layer taking 584*876*three (i.e. 584 pixels width and 876 tallness, and three since pictures have profundity three, the shade channels) on the grounds that they enter the size of the image. Channels of 3x3 grid will slide over all the spatial areas. The convolutional layer includes an *immovable of unbiased channels*. Each channel out is freely convolved with the photograph bringing about 32 capacity maps.

5.2 Activation ReLU

The Corrected Linear Unit (ReLU) is the most extreme utilized initiation work inside the world at the present time. It is deployed in practically all convolutional neural systems or profound learning. ReLU is a *non-linear activation function* employed in multi-layer neural networks or deep neural networks.

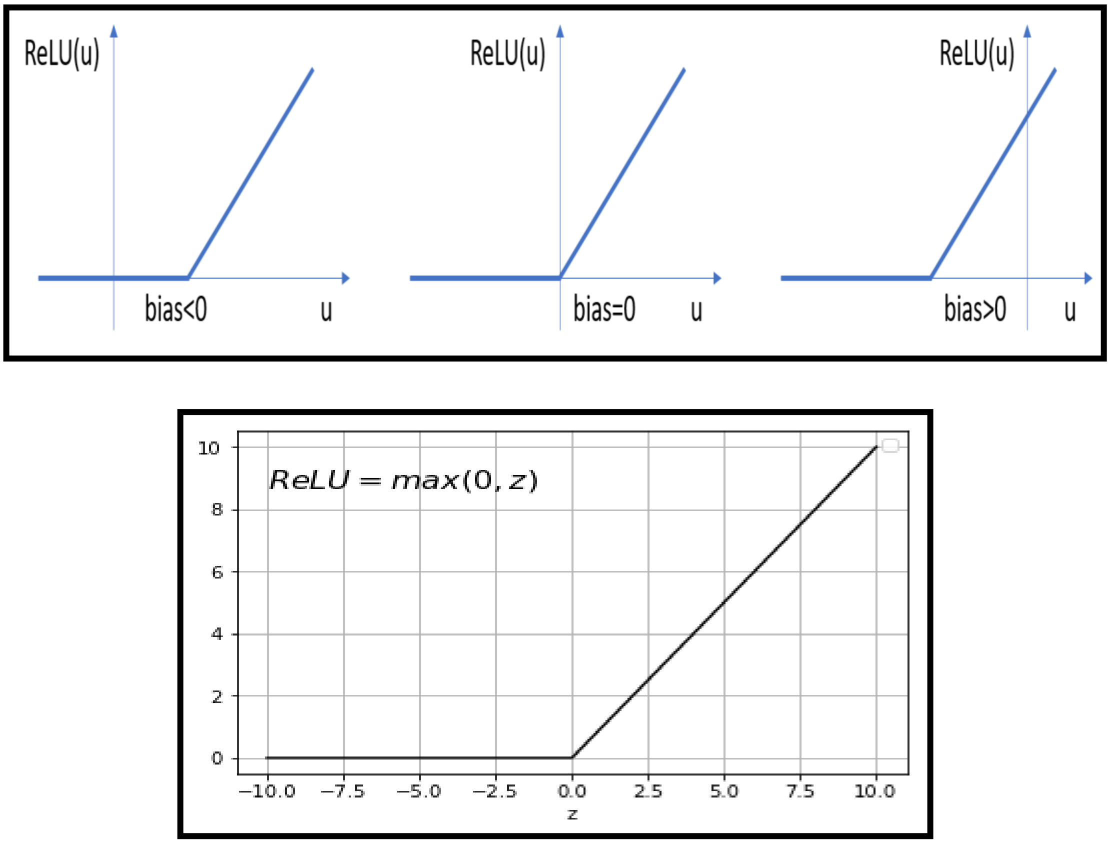


Fig.9 Graphical portrayals of ReLU.

Evidently in **Fig. 9** (lower image), the ReLU is 1/2 amended (from base). *F(z)* is 0 while *z* is significantly less than 0 and *f(z)* is equivalent to *z* when *z* is above or same to zero.Fig.9 shows the Graphical portrayals of ReLU.

5.3 Max-pooling Layer

In the Max-pooling layer the greatest *weighted capacity* is separated; this is done by changing above 2*2 grid to an increasingly packed lattice. The above 2*2 framework is changed into a grid which includes the absolute best weighted capacity that is available in 2*2 lattices. Fig .10 shows the Max pooling layer which is given below.

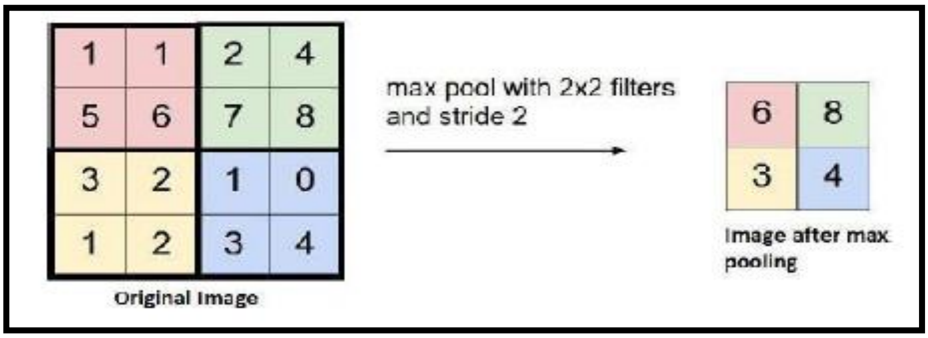


Fig. 10 Max pooling Layer

5. 4 Straightening or flattening Layer

The Straightening layer changes over the 1*3 framework for the image into one unmarried measurement exhibit which enters the thick layer. During the operation of a neural network, the enter portrayal is levelled into a *capacity vector* and passed through a network of neurons to anticipate the yield probabilities. The accompanying picture portrays the pulling down activity. The columns are linked to shape a long trademark vector. In the event, that more than one info layers are available, its columns are additionally linked to frame a reasonable longer trademark vector. The capacity vector then proceeds through more than one thick layer.

At each thick layer, the component vector is duplicated by utilizing the layer's loads, with its biases, and passed via a non-linearity. Fig.11 shows the Flatten layer which is given below.

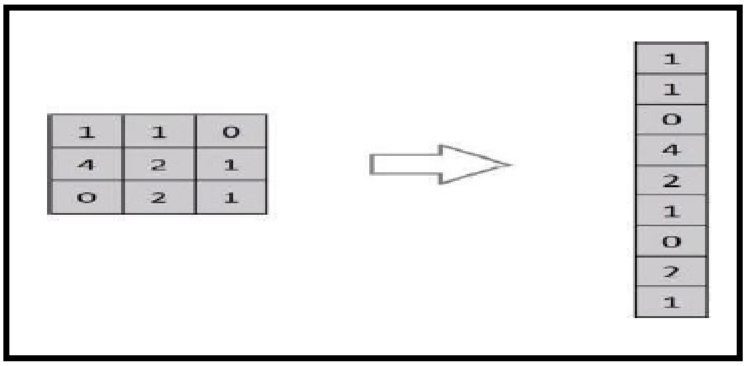


Fig-11: Flatten Layer

5.5 Softmax

The softmax highlight is an extra summed up strategic enactment included which is utilized for 1*3 multiclass classifications. Softmax is executed through a neural network layer only sooner than the yield layer. The Softmax layer must have the indistinguishable assortment of hubs as the yield layer. Softmax expands this thought into a multi-class world. That is, Softmax allocates decimal probabilities to each heaviness in a multi-class issue. Those decimal probabilities should transfer up to 1.0. This extra imperative assists in instruction by merging more quickly than without this feature.

5.6 Yield or Output layer

This is a definitive layer that creates the yield of the network is a softmax layer or sigmoid neuron, contingent upon the unravelling task - parallel or multiclass grouping.

6 IMPLEMENTATION DETAILS

6.1 Advancements utilized

Python 3.5.4: Python is a deciphered elevated level programming language for general-cause programming. Introduced by Dutch computer scientist, G. van Rossum [32], Python has a format reasoning that accentuates code meaningfulness and the utilization of significant whitespace. It enables clean programming on both small and enormous scales. Several libraries are available for Python programming including the Keras library: which is a high-arrangement neural system API, written in Python and successfully runs on apex of Tensor Flow, CNTK, or Theano. It is a cutting-edge programming environment with an emphasis on empowering fast experimentation. An excellent perspective of Python capabilities is given in Guttag [33].

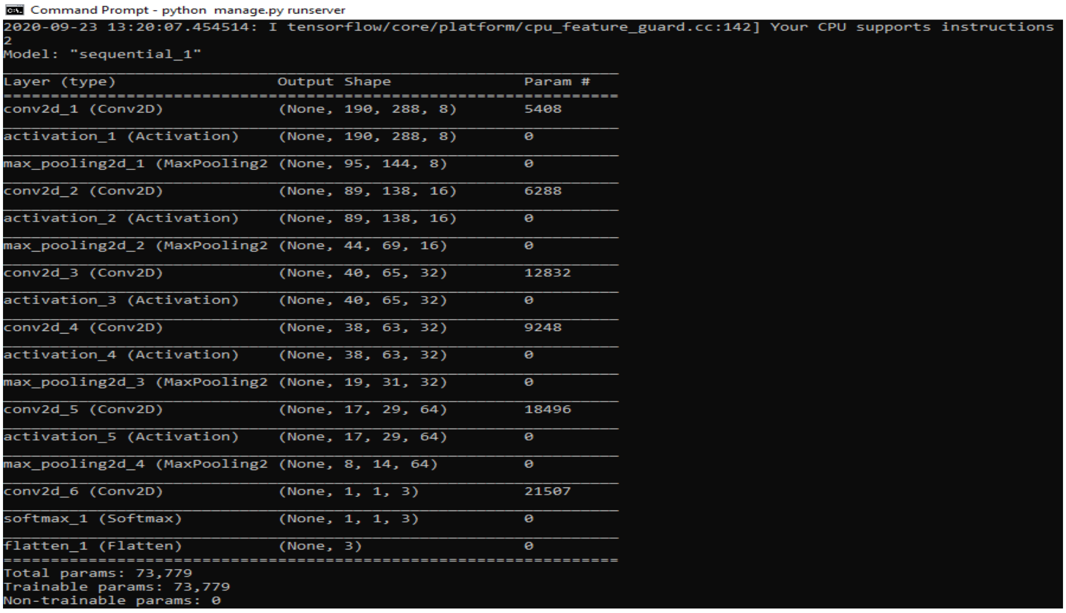
6.2 Utilizations of Python Web Applications

One can make versatile Web Apps via the utilization of structures and CMS (Content Management System) which may be developed on Python. There are also several libraries to be accessed in Python for clinical and numeric registering. These include SciPy and NumPy which are utilized when all is completed in intention registering. It is an extraordinary language with many beneficial capacities. However, it is also one of the least difficult computational languages to learn owing to its simple to-utilize punctuation.

6.3 7. RESULTS AND DISCUSSION:

A) HRF Fundus Image Dataset

This database has been set up through a community-oriented research organization to help proximate investigations on automated division calculations of retinal fundus pictures. The database may be iteratively broadened, and the website page may be improved. It is extremely useful in aiding specialists with the appraisal of division calculations. The authors encourage all individuals working with division calculations who found our database helpful to send us their assessment results. Along these lines the authors may intensify the database of calculations with the offered outcomes to keep up it continually updated. The database might be utilized freely and being an open database conveys *current* test pictures of empowering sufferers, test picture of patients with diabetic retinopathy and test photos of glaucomatous patients. Standard pictures are available for each picture.



```
Command Prompt - python  manage.py runserver
2020-09-23 13:20:07.454514: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions
2
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 190, 288, 8)       5408
_________________________________________________________________
activation_1 (Activation)    (None, 190, 288, 8)       0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 95, 144, 8)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 89, 138, 16)       6288
_________________________________________________________________
activation_2 (Activation)    (None, 89, 138, 16)       0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 44, 69, 16)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 40, 65, 32)        12832
_________________________________________________________________
activation_3 (Activation)    (None, 40, 65, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 38, 63, 32)        9248
_________________________________________________________________
activation_4 (Activation)    (None, 38, 63, 32)        0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 19, 31, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 17, 29, 64)        18496
_________________________________________________________________
activation_5 (Activation)    (None, 17, 29, 64)        0
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 14, 64)         0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 1, 1, 3)           21507
_________________________________________________________________
softmax_1 (Softmax)          (None, 1, 1, 3)           0
_________________________________________________________________
flatten_1 (Flatten)          (None, 3)                 0
=================================================================
Total params: 73,779
Trainable params: 73,779
Non-trainable params: 0
```

Fig 12 shows the Check the system performance of based file changes in state. Reloader with trained parameter and tested parameters

Fig 13 shows the patients name, patients Id, patients Prescription Id, and patients scanner id

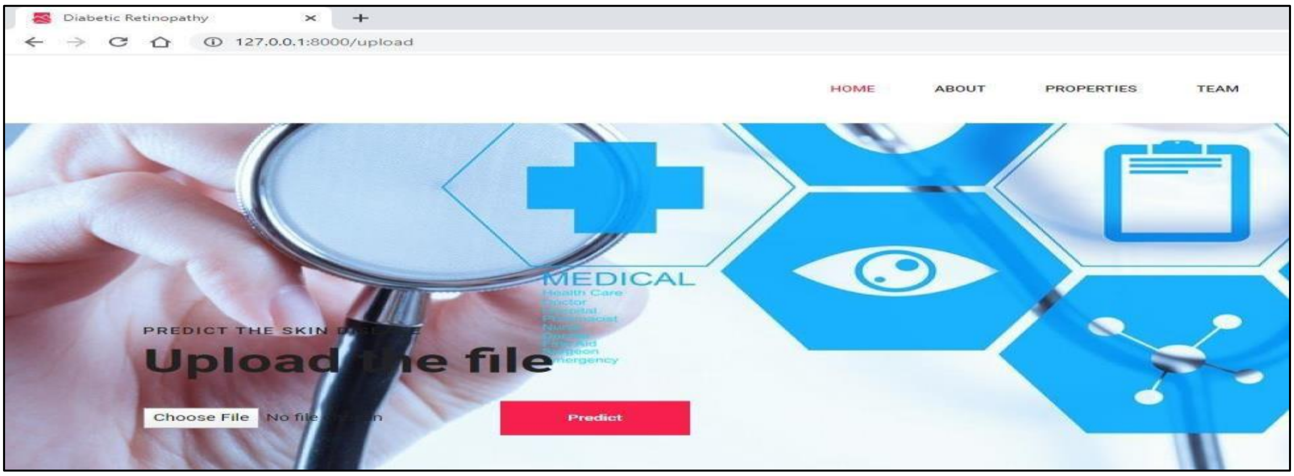


Fig 14 shows the Upload the eye images in train or test image from the dataset

Fig 15 shows the after upload the eye image click to predict

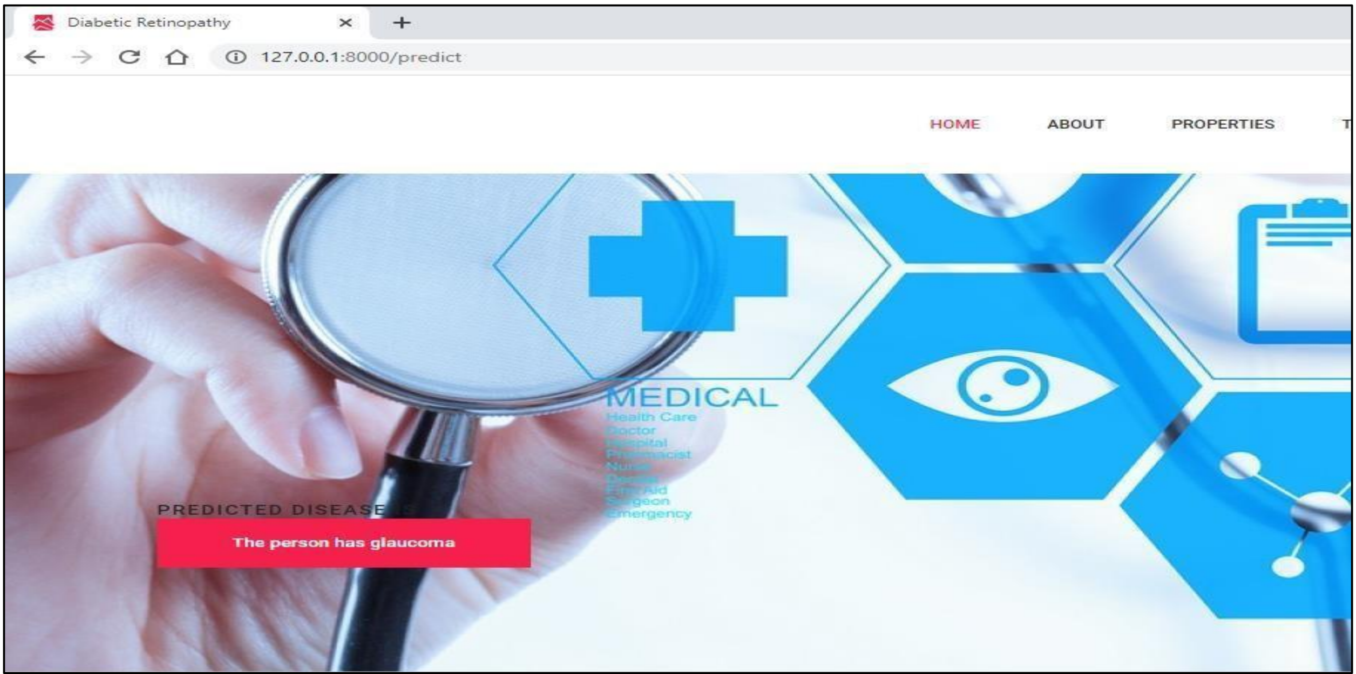


Fig 16 shows the status of patients like DR, Healthy person or Glaucoma

Validation Process: In the internal validation set, the overall sensitivity and specificity was 99.7% and 98.5% for any DR detection and 98.9% and 94.84% for Prompt referral respectively. The AUC was 0.991 and 0.969 for any DR detection and prompt referral respectively. The agreement between two observers was 99.5% and 99.2% for any DR detection and prompt referral with a kappa value of 0.94 and 0.96, respectively. In the external validation set (MESSIDOR 1), the overall sensitivity and specificity was 90.4% and 91.0% for any DR detection and 94.7% and 97.4% for prompt referral, respectively. The AUC was 0.907 and 0.960 for any DR detection and prompt referral, respectively. The agreement between two observers was 98.5% and 97.8% for any DR detection and prompt referral with a kappa value of 0.971 and 0.980, respectively. The prevalent issue confronted through DR-influenced sufferers is that they might be ignorant concerning the malady until the progressions inside the retina reaches a level that treatment will in general be less beneficial. Mechanized screening methods for DR identification achieve exceptional reduction in cost, time and work. The screening of diabetic sufferers for the advancement of diabetic retinopathy can diminish the risk of visual deficiency by 50%. With the expansion in the charge of the sufferers stricken by the illness there is *even more requirement for programmed structures* to take charge since the quantity of ophthalmologists is likewise now not adequate to manage all patients, specifically in country districts or if the outstanding task at hand of nearby ophthalmologists is overwhelming. Consequently, *programmed early discovery* could confine the seriousness of the illness and help ophthalmologists in examining and treating the confusion all the more proficiently. After designing the CNN separately, features from the six layers are concatenated for better performance. The system is tested using single images and the trained model of all the neural networks are loaded as single images tested. Next one designs the computer interpret 45 unknown images and this yields an accuracy of 97.02%. An impressive feature is that is that the incorrect predictions look very close to what the computer thought predicted.

A *confusion matrix* table can be used for the description of the performance of a classification model (or "classifier") based on test data values. The appropriate definitions are:

True positive values (TP): These are the cases in which we predicted yes (they have the disease), and they **do have** the disease.

True negative values (TN): We predicted **no**, and they **do not** have the disease.

False positive values (FP): We predicted **yes**, but they **do not** actually have the disease. (Also known as a "Type I error.")

False negative values (FN): We predicted **no**, but they actually **do have** the disease. (Also known as a "Type II error.")

$$SE = TP/(TP+FN) \qquad SP = TN/(TN+FP)$$

$$Accuracy = (TP+TN)/(TP+TN+FP+FN)$$

$$Precision = TP/(TP+FP) \qquad (1)$$

LOSS: Evaluate the loss based on training and validation and define its inter-operation by how well the model is doing for these two sets. The lower the loss the better the model.

ACCURACY: Model accuracy is determined after learning the model parameters are fixed and *no learning* is taking place. Mistakes are found based on the test samples are fed to the model, after the comparison of the true targets. Finally the percentage of *misclassification* is calculated.

The fundamental addition of our model is that it does not have to accommodate other setbacks which diverse recorded methods do and comparatively the obtained weight can be calibrated while handling the exceptions. s: 0-diabetes retinopathy patients 1 - sound patients 2 - glaucoma patients. With the correct advancement, the current CNN methodology could achieve exceptional precision - as much as 97.66% *which is superior to anything the offered presently in other methodologies* e.g. Fine KNN, Medium KNN, and Quadratic SVM anyway sub-par than weighted KNN, cubic SVM and Bayesian Logistic Regression. The comparison is summarized in **Table3**: Table 3 shows the percentage of accuracy of CNN method compared with other techniques for DR imaging.

Method	**Accuracy**
CNN (current study)	97.02%
Random Forest	91.2%
Decision Tree	85.2%
Logistic Regression	74.28%
Naïve Bayesian	75.9%
Support Vector Machine	53.2%

Table 3: Percentage of accuracy of CNN method compared with other techniques for DR imaging.

Table 4 provides results of classification and Fig. 12 provide Model accuracy which gives the details of the CNN accuracy achieved in this study.

Number of trained images	Number of tested images	Classification images	Accuracy
45	15	3	97%

Table 4 Results of Classification

```
 - 13s - loss: 0.4668 - acc: 0.8222 - val_loss: 0.3768 - val_acc: 0.8462
Epoch 38/50
 - 13s - loss: 0.3460 - acc: 0.8667 - val_loss: 0.5160 - val_acc: 0.7692
Epoch 39/50
 - 13s - loss: 0.5294 - acc: 0.7778 - val_loss: 0.4233 - val_acc: 0.8462
Epoch 40/50
 - 13s - loss: 0.4158 - acc: 0.8444 - val_loss: 0.3793 - val_acc: 0.8462
Epoch 41/50
 - 13s - loss: 0.3827 - acc: 0.8444 - val_loss: 0.4307 - val_acc: 0.8462
Epoch 42/50
 - 13s - loss: 0.3668 - acc: 0.8444 - val_loss: 0.2814 - val_acc: 0.8462
Epoch 43/50
 - 13s - loss: 0.2916 - acc: 0.8444 - val_loss: 0.1809 - val_acc: 1.0000
Epoch 44/50
 - 13s - loss: 0.2343 - acc: 0.9556 - val_loss: 0.2460 - val_acc: 0.9231
Epoch 45/50
 - 13s - loss: 0.2760 - acc: 0.8889 - val_loss: 0.1510 - val_acc: 1.0000
Epoch 46/50
 - 13s - loss: 0.2212 - acc: 0.9111 - val_loss: 0.1709 - val_acc: 0.9231
Epoch 47/50
 - 13s - loss: 0.1468 - acc: 0.9333 - val_loss: 0.1383 - val_acc: 1.0000
Epoch 48/50
 - 13s - loss: 0.1759 - acc: 0.9556 - val_loss: 0.1113 - val_acc: 1.0000
Epoch 49/50
 - 13s - loss: 0.1404 - acc: 0.9556 - val_loss: 0.2674 - val_acc: 0.9231
Epoch 50/50
 - 13s - loss: 0.1590 - acc: 0.9556 - val_loss: 0.3087 - val_acc: 0.8462
```

Fig 16 shows the accuracy and loss values

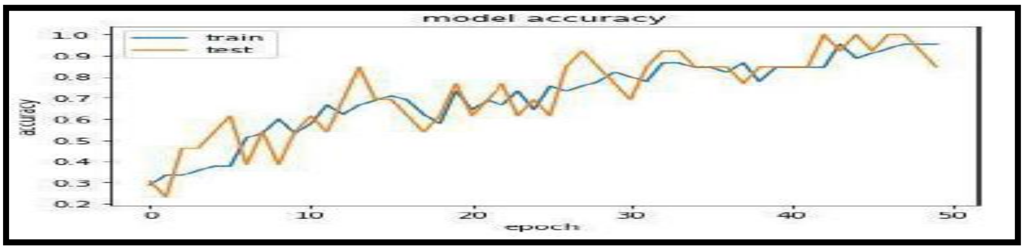


Fig. 17 Model Accuracy

The figure 17 shows the accuracy of a model is usually determined after the model parameters are learned and fixed with no learning is taken place. An accuracy of trained and tested model is used to measure the Convolutional neural network algorithm's performance in a determined learned and fixed one is taken place. The accuracy of a model is usually determined after the model parameters and is calculated in the form of a percentage. It is the measure of accurate your model's prediction is compared to the true data with trained with tested to calculated. The trained sample with parameter with images. Then the test samples are fed to the model and the number of mistakes (zero-one loss) the model makes is recorded, after comparison to the true targets. Then the percentage of misclassification is calculated.

The CNN model loss is visualized in Fig. 18 below.

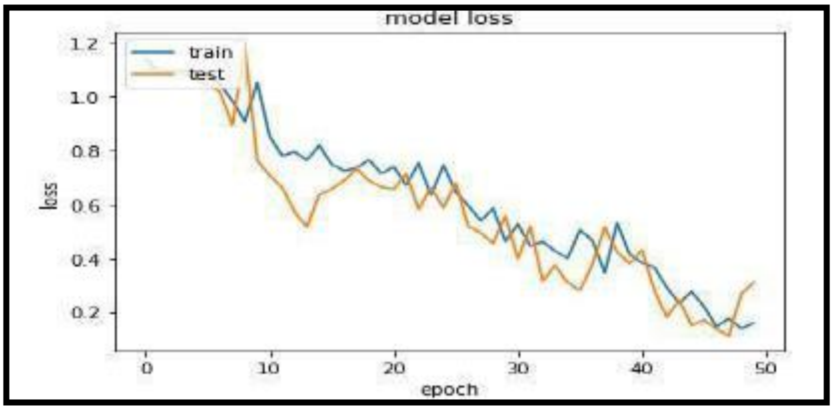


Fig. 18 Model Loss

Fig 18 gives the loss of model. A loss function is used to optimize a convolutional neural network algorithm. The loss is calculated based on training and validation and its interpretation is based on parameter model is doing in these two sets of trained and tested model. It is the sum of errors made for each example in training or validation sets. Loss value implies how poorly or well a model behaves after each iteration of optimization. The loss is calculated on training and validation and its interoperation is how well the model is doing for these two sets. It is a summation of the errors made for each example in training or validation sets.

8. CONCLUSIONS

With increasing diabetic population and a growing supply-demand gap in trained resources, AI is the future for early identification of DR and reducing blindness. A key achievement of the current CNN study is that we can rapidly identify Diabetic Retinopathy (DR) with high precision from the convolutional neural network. The deep machine learning developed will help to reduce the damage caused by diabetic retinopathy earlier in clinical treatments. The proposed neural network machine platform will give faster and more accurate assessment of patient eyes and will help medicinal specialists to make accelerated diagnoses. The device might be furthermore upgraded by utilizing tutoring and analysing the convolutional neural network. Though the proposed framework performs well it can be additionally improved by utilizing enlarged convolution instead of typical convolution which prompts less calculation. Furthermore, increasingly proficient calculations such as weighted KNN, cubic SVM and Bayesian Logistic Regression can be embedded to improve precision. In the platform we were able to build an artificial convolutional neural network which can recognize images with an accuracy of 78% using Tensor Flow. We did so by pre-processing the images to make the model more generic, split the dataset into a number of batches and finally build and train the model. Being cognizant with emerging and future technology in mobile (smart cellular) phone a possible future scope of our project is the exploration of mobile applications for diabetic retinopathy. Potentially individuals could be empowered to check diabetic issues by clicking and uploading image of the retina, yielding *instantaneous diagnoses* on DR. This possible pathway would be a novel mobile phone application termed, EYENET in which patients merely upload the image of retina, learn the DR result a and thereafter seek further medical consultation, if warranted, for appropriate treatment. This would be robust, simple and very effective towards *controlling and monitoring in real-time* the diabetic problem.

Fig. 19: DR imaging platform

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