

AUTOMATED DETECTION OF DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORKS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

by

Names of all the students with register Number

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SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC**

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this project report is the bonafide work of **PADMANABHUNI RAHUL SUDHEER KUMAR(37110531), PASUMARTHI NAGA LAKSHMAN SOWRYA(37110548)** who carried out the project entitled "**AUTOMATED DETECTION OF DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORKS**" under my supervision from **November-2020 to April-2021**.

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DECLARATION

IPADMANABHUNI RAHUL SUDHEER KUMAR(37110531) hereby declare that the Project report **“AUTOMATED DETECTION OF DIABETIC RETINOPATHY USING CNN”** done by me under the guidance of **Ms. Keerthi Samhitha.**, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

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ABSTRACT

A rule based classifier is widely applied in breast cancer diagnosis. The classifier with a good performance of disease classification have been developed and highly required over the past decades. The good classifier equips with high accurate classification rules obtaining from historical diagnosis. Since each diagnosis consists of a large amount of data features, it challenges to build minimal high accurate classification rules from such historical data. Since classification rules are derived from previous diagnosis with a large amount of features, it challenges to build a minimal number of rules with high performance while retaining all diagnosis information. Therefore, this paper aims at finding the best performance classifier giving minimal classification rules. Based on experiment result on Breast Cancer data set, the J48 decision tree classifier is found to be the best among the three classifiers: J48 decision tree, Reduced Error Pruning Tree, and Random Tree.

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LIST OF ABBREVIATIONS

CNN	–	CONVOLUTIONAL NEURAL
DR	–	NETWORK. DIABETIC RETINOPATHY.
ETDR	–	EARLY TREATMENT DIABETIC RETINOPATHY.
RELU	–	RECTIFIED LINEAR UNIT.
ROC	–	RECEIVER OPERATING
SCE	–	CHARACTERISTICS. SERVERSIDE
T2DM	–	CAPTURING ENGINE.
UKPD	–	TYPE 2 DIABETES MELLITUS.
UML	–	UNITED KINGDOM PROSPECTIVE DIABETIS.

UNIFIED MODELING

LANGUAGE. VADT	–	VETERANS
AFFAIRS. DIABETES TRIAL.		

CHAPTER

1I

NTRODUCTION

1.1OVERVIEWOFTHE PROJECT

Diabetic retinopathy (DR) is a common complication of diabetes associated with retinal vascular damage caused by long standing diabetes. Furthermore, the diagnosis of DR mostly depends on the observation and evaluation to fundus photographs of which procedure can be time-consuming even for experienced experts. Therefore computer aided automated diagnosis approaches have great potential in clinical to accurately detect DR in a short time which can further help to improve the screening rate of DR and reduce the number of blindness. For a deep learning model, the most important parts that should be focused on are data set, network architecture and training method. Before being used to train our model, fundus images data set obtained from public resources is pre processed and augmented. The model accepts two fundus images corresponding to the left eye and right eye as inputs and then transmits them into the Siamese-like blocks. The information from two eyes is gathered into the fully connected layer and finally the model will output the diagnosis result of each eye respectively.

EXISTING METHOD

Besides a binocular model for the five class DR detection task is also trained and evaluated to further prove the effectiveness of the binocular design. The result shows that, on a 10% validation set, the binocular model achieves a kappa score of 0.829 which is higher than that of existing non ensemble model. Finally the comparison between confusion matrices obtained through models with paired and unpaired inputs is performed and it demonstrates that the binocular architecture does improve the classification performance.

The Healthcare trade usually clinical diagnosis is ended typically by doctor's knowledge and practice. Computer Aided Decision Support System plays a major task in medical field. Data mining provides the methodology and technology to alter these mounds of data into useful information for decision making. By using data mining techniques it takes less time for the prediction of the disease with more accuracy. Among the increasing research on heart disease predicting system, it has happened to significant to categories the research outcomes and gives readers with an outline of the existing heart disease prediction techniques in each category.

PROPOSEDMEHOD

For a deep learning model, the most important parts that should be focused on are data set, networkarchitectureandtrainingmethod.Beforebeingusedtotrainourmodel,fundusimages datasetobtained from public resources is pre processed andaugmented. The model accepts two fundusimages corresponding to the left eye and right eye as inputs and then transmits them into the Siamese-like blocks. The information from two eyes is gathered into the fully-connected layer and finally themodelwilloutputthe diagnosisresulttofeacheayerespectively.

CHAPTER 2 LITERATURE SURVEY

The overall image processing techniques include image segmentation, feature extraction and classification. For image segmentation, wide research has been carried out based on Region growing method which is a model based approach. The proposed CAD system in the thesis performs segmentation using Kirsch's template which is based on neighboring pixels. The proposed CAD system uses Morphological method for feature extraction. Morphological features like Area, No. of regions, Eccentricity, Extent, Orientation, Convex area of the polygon, Solidity has been extracted. Classifiers and neural network approach has been frequently used for image classification. In the proposed CAD system classification has been done using SVM classifier which is a neural network approach. Hence a detailed literature survey has been carried out focusing on all the above three topics.

Morphological Processing

The most frequently used method for finding of hemorrhages is an image morphology method. It is a set of operators that transform images into size, shape, connectivity, etc. The basic morphological operators are erosion, dilation, opening and closing. Shivaram et al [22] have utilized image mathematical morphology methods for identification of the hemorrhages and subduing the blood vessels. The outcomes of their method were compared at the pixel level with ophthalmologist's hand-drawn ('ground truth') images.

Drawback: The method proposed to directly extract the morphological features of the hemorrhages, did not envisage the performance of blood vessel detection as false positive and false negative components. The results obtained by means of sensitivity were less which needs to be improved. Karnowski et al [23] have proposed a morphology based reconstruction technique for segmentation of retinal lesion. The segmentation procedure was implemented at different scales using 'ground truth' data to segment out nuisance blobs from the actual lesions. In their research, they created a synthetic feature vector (lesion population) from each and every image to distinguish normal and abnormal classes.

Data mining tools can answer trade questions that conventionally in use much time overriding to decide. In this paper we study different papers in which one or more algorithms of data mining used for the prediction of heart disease. As of the study it is observed that Fuzzy Intelligent Techniques increase the accuracy of the heart disease prediction system. The generally used techniques for Heart Disease Prediction and their complexities are summarized in this paper. A popular saying goes that we are living in an "information age". Terabytes of data are produced every day. Data mining is the process which turns a collection of data into knowledge. The health care industry generates a huge amount of data daily. However, most of it is not effectively used. Efficient tools to extract knowledge from these databases for clinical detection of diseases or other purposes are not much prevalent. The aim of this paper is to summarize some of the current research on predicting heart diseases using data mining techniques, analyse the various combinations of mining algorithms used and conclude which technique(s) are effective and efficient.

Drawback: Oversegmentation of the imagery occurs which affects the true positive components (true lesions). Post processing needs to be done for the ground truth image to remove the nuisance blob from the true lesions.

Similarly, Kande et al [24] – [25] proposed a detection technique of hemorrhage and Micro-aneurysms by utilizing mathematical morphology and pixel classification. The candidates with red lesion were identified using the morphological top-hat transformation method and matched filter. Finally, the Support Vector Machine (SVM) was applied to classify the non-red lesion areas and red lesion areas with 89 retinal fundus images selected randomly from 3 databases DIARETDBI [26], DIARETDBO and STARE [27].

Similarly, a few other groups (Matei et al [29] and Langroudi and Sadjedi [30]) have also utilized morphological operations and thresholding technique to identify hemorrhages and blood vessels. In [31], they propose MML-TH (maximum of multiple linear top hats) method by utilizing multi-scale procedures to identify the hemorrhages and regions growing around them. Then, local vessel detection was performed using thresholding based segmentation and skeletonizing the segments. Finally, the blot hemorrhages were classified using the SVM classifier.

Drawback: The accuracy of this method is inconsiderable for Blot Hemorrhages (BH) greater than or equal to 1. When the lesion size varies on a continuous scale, difficulty arises in distinguishing BH from smaller dark lesions. Acharya et al [32] have proposed the morphological method with “Ball” shaped structuring elements for detecting hemorrhages by removing the blood vessel from hemorrhage candidates. Another research group proposed mathematical morphological and fuzzy clustering methods for blood vessel extraction from retinal fundus images [33]. The micro-aneurysms and hemorrhages were detected successfully by suppressing fovea as well as blood vessels

We are in a period of “Information Age” where the traditional industry can pressure the rapid shift to the industrial revolution for industrialization, based on economy of information technology. Terabytes of data are produced and stored day-to-day life because of fast growth in „Information Technology“. Terabytes of data are produced and stored day-to-day life because of fast growth in „Information Technology“. The data which is collected is converted into knowledge by data analysis by using various combinations of algorithms. For example: the huge amount of the data regarding the patients is generated by the hospitals such as x-ray results, lungs results, pain results, chest pain results, personal health records (PHRs), etc. There is no effective use of the data which is generated from the hospitals. Some certain tools are used to extract the information from the database for the detection and other functions is not accepted. The main theme of the paper is the prediction of heart diseases using machine learning techniques by summarizing the few current researches. In this paper, the logistic regression algorithm is used and the health care data which classifies the patients whether they are having heart diseases or not according to the information in the record.

People with diabetes have an increased risk of developing a number of serious health problems. Consistently high blood glucose levels can lead to serious diseases affecting the heart and blood vessels, eyes, kidneys, nerves and teeth. In addition, people with diabetes also have a high risk of developing infections. In almost all high-income countries, diabetes is a leading cause of cardiovascular disease, blindness, kidney failure, and lower limb accumulation.

Maintaining blood glucose levels, blood pressure, and cholesterol at or close to normal can help delay or prevent diabetes complications. Therefore people with diabetes need regular monitoring.

Drawback: Extraction of blood vessels was not performed. Similarly, the performance analysis to find the sensitivity and specificity were not carried out. Niemeijer et al [34] have proposed a hybrid approach for the detection of red lesions present in the retinal fundus images. The red ones were extracted by mathematical morphology method and the k-Nearest Neighbor (kNN) classifier was used for the classification of red lesion and non-red lesion candidates.

Drawback: The larger red lesions were not completely segmented. A fewer number of image features were considered for classification, which produced comparatively lesser accuracy.

Neural Network Approaches

Neural networks are similar to biological neurons, which consist of a set of adaptive weights and are capable of approximating nonlinear functions of their inputs. Supervised learning, unsupervised learning and reinforcement learning are the three types used in

Neural Networks. Gardner et al [35] proposed an approach for detection of diabetic features from digital fundus images using a back propagation neural network. The input images were divided into sub-images of 30 x 30 and 20 x 20 pixels used as training data and test data for the network. The features extracted from each sub-image

were used to classify them into (i) normal, (ii) vessel, (iii) exudate and (iv) hemorrhage. The study outcome revealed that the detection rate for the hemorrhage was 73%.

Drawback: The outcome rate reported for the detection of hemorrhage was of comparatively small compared to acceptable levels. Yet another study by Usher et al [36] employed a neural network for detection of diabetic features. The micro-aneurysms and hemorrhages were successfully spotted using iterative region growing and adaptive thresholding in combination with a "moat operator" as well as edge enhancement operators.

Drawback: The specificity obtained by the system was very small, which is below 50%. When the system attempts to increase in the specificity, the sensitivity gets reduced. In [37], the research group has proposed a color and shape based feature extraction technique using morphological operations and region growing method with logistic regression for selection. In the neural network classification, a multilayer perceptron with radial basis function was utilized and majority voting was used to detect red lesions.

Diabetes can cause damage to the nerves throughout the body when blood glucose and blood pressure are too high. This can lead to problems with digestion, erectile dysfunction, and many other functions. Among the most commonly affected areas are the extremities, in particular the feet. Nerve damage in these areas is called peripheral neuropathy, and can lead to pain, tingling, and loss of feeling.

Loss of feeling is particularly important because it can allow injuries to go unnoticed, leading to serious infections and possible amputations. People with diabetes carry a risk of amputation that may be more than 25 times greater than that of people without diabetes. However, with comprehensive management, a large proportion of amputations related to diabetes can be prevented.

Drawback:

The specificity value obtained is very small just 52%. Garcia et al [38] have utilized a multilayer perceptron neural network in order to spot the red lesions within the retinal fundus images. The approach was validated on 50 retinal fundus images with a set of 29 features which describes about parameters such as the color and shape of image regions.

Drawback: The specificity value achieved is small just 60%.

Classifiers

Image classifiers classify the data into categories based on the numerical properties of various image features. Training and testing are the two processes done by classification algorithm.

Drawback: The proposed system could not detect any Hemorrhages, not even the blood vessels. In [41], the research group has proposed a gray level grouping based contrast enhancement technique in order to improve the contrast of the green channel. Then, the candidate's red lesions were spotted by applying automatic seed detection. The Gaussian mixture models and k-Nearest Neighbor (kNN) classifiers were joined and called Hybrid classifier. It was utilized to distinguish the non-red lesions from the actual red lesions.

Drawback: Small red lesions were not properly detected. Tan et al [42] introduced the watershed algorithm for segmenting splat regions which are a group of pixels with related color and spatial position. The connected vascular structures were removed by utilizing an automated vessels extraction technique. Then, the kNN classifier was applied along with 42 image features in training and further reduced to 7 image features by forward feature selection procedures in the testing state. Further, a set of 20 retinal fundus images from DRIVE database [43] were utilized for training the classifier and 1200 images from MESSIDOR database [44] were utilized in testing the classifier.

Most people with diabetes will develop some form of eye disease (retinopathy) causing reduced vision or blindness. Consistently high levels of blood glucose, together with high blood pressure and high cholesterol, are the main causes of retinopathy. It can be managed through regular eye checks and keeping glucose and lipid levels as close to normal. Women with any type of diabetes during pregnancy risk a number of complications if they do not carefully monitor and manage their condition. To prevent possible organ damage to the fetus, women with type 1 diabetes or type 2 diabetes should achieve target glucose levels before conception. All women with diabetes during pregnancy, type 1, type 2 or gestational should strive for target blood glucose levels throughout to minimize complications.

Drawback:

The performance of overall approach was slower than that of any advanced classifier such as SVM, as it has inherent features reduction capabilities. Zhang and Chutatape [45] have proposed the top-down approach for dark lesion detection and the bottom-up approach in order to detect bright lesions within the retinal fundus images. In the hemorrhage detection, the hemorrhages are situated in the Region of Interest (ROI) primarily by computing the evidential value of each and every pixel using SVM with a kernel and principal component analysis (PCA). The PCAs were used for reducing the features.

Drawback: Vessel detection and Optic Disk detection have not been done.

Region Growing

Region Growing is a simple image segmentation method in which classification is done on region based and pixel based methods. This method of segmentation examines neighboring pixels and determines whether this pixel should be added to the region of interest. Sinthana yothin et al [17], [46] have investigated an adaptive thresholding and a "moat operator" for increasing the contrast levels of the lesions by enhancing the edge regions. The red lesions were successfully segmented by using an iterative region-growing technique and then a neural network was utilized for segmenting out the blood vessels from hemorrhages within the retinal region. They have utilized the matched filter based on 3 major properties in order to segment out the blood vessels and then utilized tracking algorithm to identify hemorrhages.

Drawback: The proposed approach is not directly applicable for any clinical situation, because, these sensitivity and specificity data are detected for individual lesions of the image. Bae et al [47] have proposed a hybrid method for detection of hemorrhages from retinal fundus images. The hemorrhage candidates successfully extracted by utilizing a circular shape template matching with normalized cross correlation technique. The hemorrhages were then segmented out by 2 methods of region growing: (i) region growing segmentation using the local thresholding and (ii) adaptive seed region growing segmentation. The system achieved a high sensitivity of 85%.

People with diabetes have an increased risk of inflammation of the gums (periodontitis) if blood glucose is not properly managed. Periodontitis is a major cause of tooth loss and is associated with an increased risk of cardiovascular disease (CVD). Regular oral check-ups should be established to ensure early diagnosis, particularly among people with previously undiagnosed diabetes and prompt management of any oral complications in people with diabetes. Annual visits are recommended for symptoms of gum diseases such as bleeding.

Drawback: Specificity has not been calculated. Detection of exudates and blood vessels has not been done. The red lesions detection technique has been proposed by Marino et al [48] had three stages. First, the red lesions candidates were obtained by utilizing a correlation filter set. This was followed by region growing technique and feature based filtering technique were applied in order to remove the false positive cases.

Drawback: The sensitivity obtained from the proposed method is just 0.79%. Validation has not been done with a bigger dataset of images.

Conclusion

Literature survey has been done based on image segmentation, feature extraction and classification. In most of the papers accuracy is poor, sensitivity is less. In some of the papers sensitivity and specificity calculation has not been carried out. They could not achieve high performance for both sensitivity and specificity.

The classic symptoms of untreated diabetes are unintended weight loss, polyuria (increased urination), polydipsia (increased thirst), and polyphagia (increased hunger). Symptoms may develop rapidly (weeks or months) in type 1 diabetes, while they usually develop much more slowly and may be subtle or absent in type 2 diabetes.

Several other signs and symptoms can mark the onset of diabetes although they are not specific to the disease. In addition to the known ones above, they include blurred vision, headache, fatigue, slow healing of cuts, and itchy skin. Prolonged high blood glucose can cause glucose absorption in the lens of the eye, which leads to changes in its shape, resulting in vision changes. Long-term vision loss can also be caused by diabetic retinopathy. A number of skin rashes that can occur in diabetes are collectively known as diabetic dermadromes.

People (usually with type 1 diabetes) may also experience episodes of diabetic ketoacidosis (DKA), a metabolic disturbance characterized by nausea, vomiting and abdominal pain, the smell of acetone on the breath, deep breathing known as Kussmaul breathing, and in severe cases a decreased level of consciousness. A rare but equally severe possibility is hyperosmolar hyperglycemic state (HHS), which is more common in type 2 diabetes and is mainly the result of dehydration. Treatment-related low blood sugar (hypoglycemia) is common in people with type 1 and also type 2 diabetes depending on the medication being used. Most cases are mild and are not considered medical emergencies. Effects can range from feelings of unease, sweating, trembling, and increased appetite in mild cases to effects such as confusion, changes in behavior such as aggressiveness, seizures, unconsciousness, and (rarely) permanent brain damage or death in severe cases. Rapid breathing, sweating, and cold, pale skin are characteristic of low blood sugar but not definitive. Mild to moderate cases are self-treated by eating or drinking something high in sugar. Severe cases can lead to unconsciousness and must be treated with intravenous glucose.

CHAPTER3

AIM OF THE PROJECT

Diabetic retinopathy (DR) is a common complication of diabetes associated with retinal vascular damage caused by longstanding diabetes mellitus. According to the research in, DR has become one of the important causes of blindness and vision impairment worldwide, since 0.4 million cases of blindness and 2.6 million cases of severe vision impairment globally can be attributed to it in 2015. In fact, the impairment of DR to vision can be controlled or averted if it is detected and treated in time. However, many patients miss the best time for treatment since there are few signs or symptoms at the early stage of DR.

SYSTEM REQUIREMENTS

HARDWARE AND SOFTWARE SPECIFICATION

HARDWARE REQUIREMENTS

- Hard Disk: 500GB and Above
- RAM : 4GB and Above
- Processor: I3 and Above

SOFTWARE REQUIREMENTS

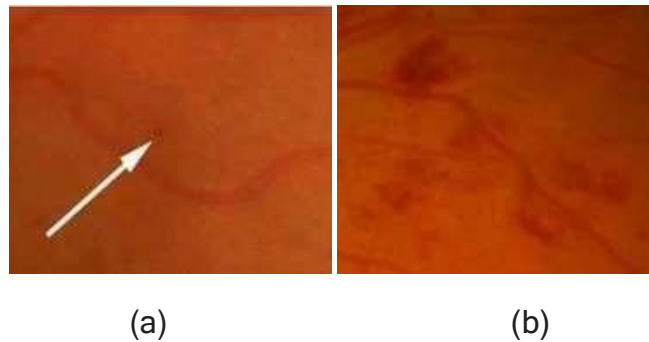
Operating System : Windows 7, 8, 10
(64bit) Software : Python 3.7
Tools : Anaconda (Jupyter Note Book

IDE) Diabetic retinopathy

In the type 1 diabetes, the insulin production is permanently damaged, whereas in the type 2 diabetes, the person is suffering from increased resistance to insulin. The type 2 diabetes is a familial disease, but also related to limited physical activity and lifestyle. The diabetes may cause abnormalities in the retina (diabetic retinopathy), kidneys (diabetic nephropathy), and nervous system (diabetic neuropathy).

The diabetic retinopathy is a complication of diabetes, causing abnormalities in the retina, and in the worst case, blindness. Typically there are no salient symptoms in the early stages of diabetes, but the number and severity predominantly increase during the time. The diabetic retinopathy typically begins as small changes in the retinal capillary. The first detectable abnormalities are microaneurysms which are local distensions of the retinal capillary and which cause intra-retinal haemorrhage when ruptured. In time, the retinal edema and hard exudates are followed by the increased permeability of the capillary walls. The hard exudates are lipid formations leaking from these weakened blood vessels. This state of the retinopathy is called non-proliferative diabetic retinopathy. However, if the above-mentioned abnormalities appear in the central vision area (macula), it is called diabetic maculopathy. As the retinopathy advances, the blood vessels become obstructed which causes microinfarcts in the retina. These microinfarcts are called soft exudate. When a significant number of soft exudates (> 6), or intraretinal microvascular abnormalities are encountered, the state of the retinopathy is defined as preproliferative diabetic retinopathy.

The preproliferative diabetic retinopathy can quickly turn into proliferative diabetic retinopathy when extensive lack of oxygen causes the development of new fragile vessels. This is called neovascularization which is a serious state threatening eye sight. The field of eye sight can be obstructed by a haemorrhage to the vitreous body which is a common cause of blindness for the type 1 diabetes. The neovascularization can tear retina, and when it is located near the center of macula, it can cause the loss of eye sight. Due to the progressive nature of the retinopathy, regular monitoring is needed after diagnosis. However, broad screenings cannot be performed due to the fact that the fundus image examination requires attention of medical experts. For the screening, automatic image processing methods must be developed.



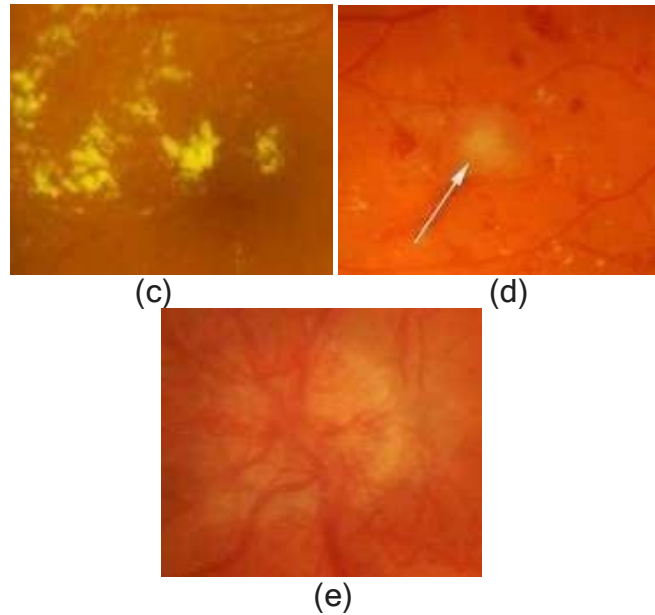


Figure 1: Abnormal findings in the eye fundus caused by the diabetic retinopathy: (a) microaneurysms (marked with an arrow), haemorrhages, (c) hard exudates, (d) soft exudate (marked with an arrow), and (e) neovascularization.

Automatic methods

As mentioned previously, the diagnosis of diabetic retinopathy can be divided into the following two categories:

Screening of the diabetic retinopathy
Monitoring of the diabetic retinopathy

Most automatic systems approach the detection directly using shape, color, and domain knowledge of diabetic retinopathy findings, but the abnormalities can also be found indirectly by detecting changes between two fundus images taken from the same eye in different time moments. The direct approach contributes to screening of the disease, where the indirect approach contributes to both screening and monitoring of the diabetic retinopathy. Both approaches use roughly the following stages for finding abnormalities in fundus images: 1) image enhancement 2) candidate diabetic retinopathy finding detection.

Some of the main features distinguishing between the different findings and normal fundus parts are the color and brightness. These same features have been verified also by ophthalmologists. Unsurprisingly these features dominate in the automatic methods, and therefore will be shortly reviewed in our brief surveys for different type of findings. Most of the automatic methods also detect normal fundus parts, such as optic disk, blood vessels, and macula. The automatic method either uses the vital domain information provided by the normal fundus parts or remove them due to their similar color and shape appearance with abnormal fundus findings. The detection of normal fundus parts is not considered in this study.

Microaneurysms and hemorrhages

Image enhancement methods: Niemeijer et al. estimated non-uniform background intensity of fundus image by applying median filtering to the green channel of the fundus image. Shade correction was generated by subtracting the result from the original green channel.

Fleming et al. had similar approach for microaneurysms, but the green channel of the original fundus image was divided with the background intensity image. In addition, the shade corrected image was normalized for global image contrast by dividing with its standard deviation. Multiple local contrast enhancement methods were tested to improve detection accuracy.

In hemorrhage detection, Zhang and Chutape used histogram specification applied to each individual RGB color component to normalize the colors between different fundus images. Sinthayothinet al. used local contrast enhancement to equalize the intensity variation in fundus images. The fundus images were transformed from RGB color model to IHS color model and the local contrast enhancement was applied to the intensity component of the image.

The primary complications of diabetes due to damage in small blood vessels include damage to the eyes, kidneys, and nerves. Damage to the eyes, known as diabetic retinopathy, is caused by damage to the blood vessels in the retina of the eye, and can result in gradual vision loss and eventual blindness. Diabetes also increases the risk of having glaucoma, cataracts, and other eye problems. It is recommended that people with diabetes visit an eye doctor once a year. Damage to the kidneys, known as diabetic nephropathy, can lead to tissue scarring, urine protein loss, and eventually chronic kidney disease, sometimes requiring dialysis or kidney transplantation. Damage to the nerves of the body, known as diabetic neuropathy, is the most common complication of diabetes.

Detection and classification methods: Niemeijer et al. extracted the candidate finding areas by assigning posterior probability of being red finding for every pixel using Gaussian filter and its derivatives as features for k-nearest neighbor clustering. Shape and intensity properties of the candidate areas were used for more accurate abnormal red finding and normal red finding classification.

Fleming et al. segmented candidate microaneurysm areas by applying region growing to image enhanced with morphological top-hat operation and thresholding. The result candidate areas were reclassified with k-nearest neighbor clustering using the shape and intensity information.

Zhang and Chutape used hemorrhage areas restricted by finite window in training images as input for support vector machine. To detect different sized hemorrhages a pyramid of images was generated by changing the resolution of fundus image. The local minima of the support vector machine provided evidence map were selected as hemorrhage locations. The principal component analysis was used to reduce the complexity of feature space.

Sinthanayothin et al. sharpened the edges of red finding regions by applying moat operator to green channel of the contrast enhanced image. From the result image, red findings were extracted with recursive region growing and thresholding.

Hard and soft exudates

Image enhancement methods: Narasimhaiyer et al. used normal retinal findings (vasculature, optic disk, fovea, and abnormal findings) to estimate the illumination component using iterative robust homographic surface fitting to compensate the non-uniform illumination in fundus images.

In detection of bright diabetic retinopathy areas from fundus images, Zhang and Chutape applied adaptive local contrast enhancement to sub-image areas using the local mean and standard deviation of intensities. The same approach was used by Osareh et al. after color normalization between fundus images using histogram specification.

Type 1 diabetes is characterized by loss of the insulin-producing beta cells of the pancreatic islets, leading to insulin deficiency. This type can be further classified as immune-mediated or idiopathic. The majority of type 1 diabetes is of the immune-mediated nature, in which a T cell-mediated autoimmune attack leads to the loss of beta cells and thus insulin. It causes approximately 10% of diabetes mellitus cases in North America and Europe. Most affected people are otherwise healthy and of a healthy weight when onset occurs. Sensitivity and responsiveness to insulin are usually normal, especially in the early stages. Although it has been called "juvenile diabetes" due to the frequent onset in children, the majority of individuals.

transform function similar to gamma correction.

Detection and classification methods: Hsu et al. determined abnormal and normal finding areas using intensity properties for dynamic clustering. From the result abnormal areas, hard exudates were separated from soft exudates and drusen using intensity contrast information between abnormal areas and immediate background. The domain knowledge of retinal blood vessels were used to remove false artifacts.

Walter et al. eliminated the vessels by applying morphological closing to the luminance component of the fundus image. From the result, within a sliding window local standard deviation image was calculated and thresholded into coarse exudate areas. More accurate contours were acquired by thresholding difference between original image and morphologically reconstructed image.

Sánchez et al. used yellowish color and sharp edges to distinguish hard exudates from the fundus images. The image pixels were classified into background and yellowish objects using minimum distance discrimination, where the contour pixels of extracted optic disk were used as background color reference and pixels inside the contour were used as yellowish object color reference. The segmented yellowish areas and their edge information extracted with Kirsch's mask were combined to hard exudate areas using boolean operator.

Zhang and Chutape located the bright abnormal regions in fundus images by applying fuzzy c-means clustering in LUV color space. The result areas were classified to hard exudates, soft exudates, and normal findings using support vector machine.

Osareh et al. searched the coarse hard exudate areas using fuzzy c-means clustering with Gaussian smoothed histograms of each color band of the fundus image. These segmented areas were reclassified to exudate and non-exudate regions using neural networks. Color, region size, mean and standard deviation of intensity, and edge strength were used as features.

Li and Chutape segmented exudates with combination of Canny edge detection and region growing in LUV color space. Gradient, mean pixel value, and seed pixel value were used as criteria in region growing.

Niemeijer et al. used a similar approach for bright abnormal region detection as they used for finding abnormal red regions in. In addition to the previous work, the prior knowledge of optic disk and vascular arch were used to improve detection.

accuracy.

Sinthanayothin et al. clustered similar pixels using intensity difference as criteria for recursive region growing. The region with the most pixels were considered as background and defined the threshold value for hard exudate areas.

Wang et al. used spherical color coordinates as features for the classification of fundus image pixels to background and bright abnormal findings using minimum distance discriminant. The abnormal findings were verified using local-window-based method.

Evaluation database

A necessary tool for the reliable evaluation and comparison of medical image processing algorithms is a database including a selected set of high-quality medical images which are representatives of the diabetic retinopathy and have been verified by experts. In addition to the images, also information about the medical findings must be available. This information of findings is called the ground truth. An accurate algorithm should take an image as input, and output a result or description which is consistent with the ground truth. In the evaluation, the consistency is measured and compared between the algorithms. In the following, we describe images and ground truth for DIARETDB0.

Fundus images

The current database consists of 130 color fundus images of which 20 are normal and 110 contain signs of the diabetic retinopathy. The images were taken in the Kuopio university hospital. The images were dedicatedly selected, but their distribution does not correspond to any typical population, i.e., the data is biased – no a priori information can be devised from it. Images were captured with few 50 degree field-of-view digital fundus cameras with unknown camera settings (flash intensity, shutter).

"Brittle" diabetes, also known as unstable diabetes or labile diabetes, is a term that was traditionally used to describe the dramatic and recurrent swings in glucose levels, often occurring for no apparent reason in insulin-dependent diabetes. This term, however, has no biologic basis and should not be used.^[42] Still, type 1 diabetes can be accompanied by irregular and unpredictable high blood sugar levels, and the potential for diabetic ketoacidosis or serious low blood sugar levels. Other complications include an impaired counterregulatory response to low blood sugar, infection, gastroparesis (which leads to erratic absorption of dietary carbohydrates), and endocrinopathies (e.g., Addison's disease). These phenomena are believed to occur no more frequently than in 1% to 2%.

speed, aperture, gain) . The images contain an unknown amount of imaging noise and optical aberrations (dispersion, transverse and lateral chromatic, spherical, field curvature, coma, astigmatism, distortion), and unknown accuracy of photometric information (color or intensity). Variance over the visual appearance of different retinopathy findings can, thus, be considered as maximal. However, The data correspond to practical situations, and can be used to evaluate the general performance of diagnosis methods. The general performance corresponds to the situation where no calibration is performed (no correspondence to the real world measurements), but where images correspond to commonly used imaging conditions, i.e., the conditions typically encountered in hospitals. This data set is referred to as “calibration level 0 fundus images”.

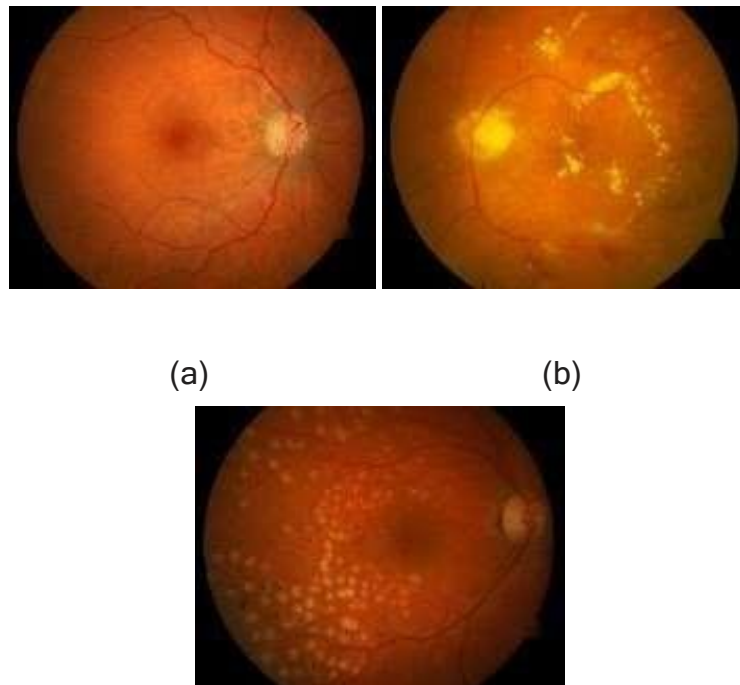


Figure 2: Fundus images: (a) normal fundus, (b) abnormal fundus, and (c) abnormal fundus after treatment by photo-coagulation.

Groundtruth

The most important accuracy measures for medical diagnosis methods are sensitivity and specificity. Sensitivity and specificity are defined on the image basis – an image either contains a specific finding or not despite the fact that the diabetic retinopathy findings do have spatial locations in the fundus . For the computer vision researchers, it is important to ensure that the automatically extracted diabetic retinopathy findings also spatially correspond to the findings marked by experts, that is, they appear at the same location in the image. Thus, the more detailed expert groundtruth contains also the description of visual appearance of diabetic retinopathy findings.

For every fundus image there is a corresponding ground truth file. A ground truth file contains all findings types found in the specific image file.

Marking visual findings

The image ground truth is based on expert-selected findings related to the diabetic retinopathy and normal fundus structures. A person with a medical education (M.D.) and specialization in ophthalmology is considered an expert.

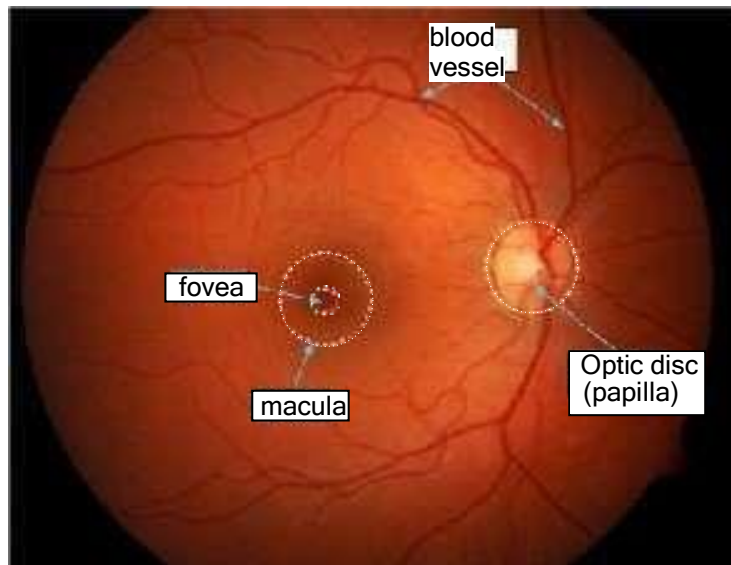


Figure 3: Structural elements of a normal fundus.

A special software tool was provided for the experts to inspect

the fundus images and annotate the findings. The user interface of the current software version. It should be noted that the workstation displays were not calibrated. Therefore, the diabetic retinopathy findings were not equally visible on all displays. However, the situation corresponds to the current best practices.

The ground truth tool provided two graphical marking directives at the time of marking and the usage was not instructed for the medical experts. This freedom of choice was allowed to prevent a biased scheme, and the medical experts were allowed to construct their own best practices to mark different findings. It was possible to use different combinations of the graphical directives for the same type of findings. Currently, the following graphical directives are:

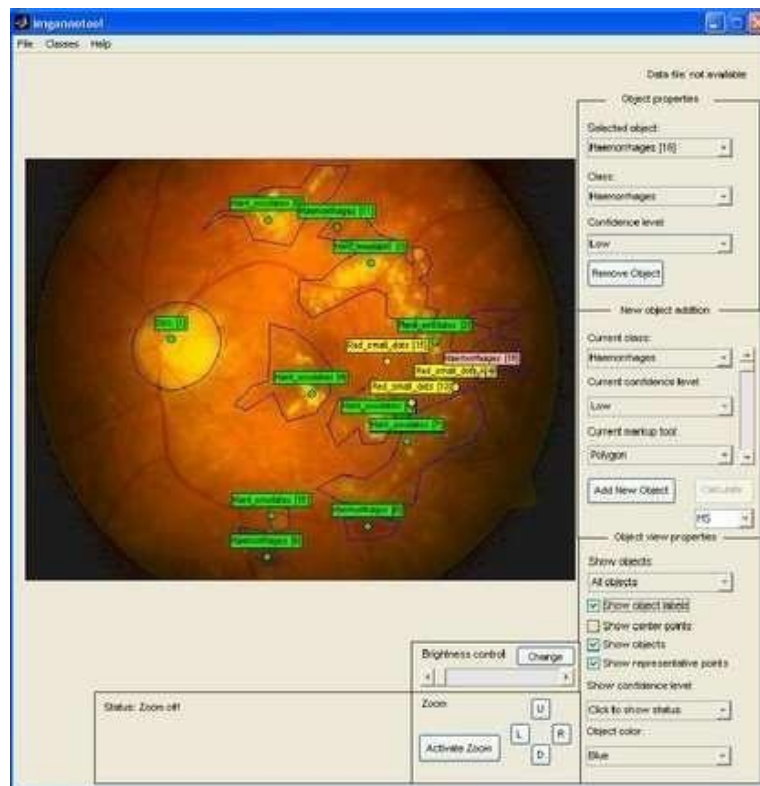


Figure 4: Graphical tool for gathering knowledge from medical experts. Centroid (Fig. 5(a)), Polygon region (Fig. 5(b)),

Circle region (Fig. 5(c)), Ellipse region (Fig. 5(c)), and Representative point (Fig. 5(e)).

In addition to the graphical directives, the image annotation tool provided a gamma correction tool and semi-automatic tool for more accurate definition of the finding areas. The semi-automatic tool used the color information provided by the representative point. In gathering the expert knowledge, the semi-automatic tool was not used.

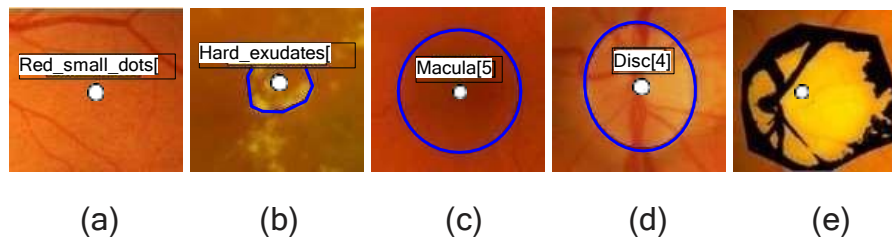


Figure 5: Graphical directives for marking the visual findings: (a) centroid; (b) polygon region; and (c) circle region; (d) semi-automatic region cropping tool and representative point.

Data format

The expert knowledge gathered with the ground truth tool is stored to a text file. Each line in the text file corresponds to a visual finding marked with the ground truth tool. The data format for visual finding is defined as

```
CENTROID[POLYGON_REGION][CIRCLE/ELLIPSE_REGION]RP_POINT REGION_TOOL
... CONFIDENCE_LEVEL FINDING_TYPE
```

Each marking in image is defined by the centroid and one other graphical directive. The same graphical directive should be consistently used for every medical finding type over the image set. The directive attributes are visualized in Fig. 6 and defined as follows:

CENTROIDX Y
 POLYGON_REGION [X_1X_2X_3...][Y_1Y_2Y_3...]CIRCLE_REGION [RADIUS]
 ELLIPSE_REGION[RADIUS1][RADIUS2][ANGLE]RP_POINT(X,Y)
 REGION_TOOL [METHOD,VALUE]CONFIDENCE_LEVEL
 HIGH,MEDIUM,LOWFINDING_TYPE
 RED_SMALL_DOTS,HARD_EXUDATES...

Verifyingimagequality

Representativequalityofthedatabaseimagesvariesduetotheuncalibratedimagingenvironment. The vaguely defined practices in imaging and challenging imaging geometry ofthe fundus cause partial over and under exposures in digital images which can still be used forthe diagnosis. A method for evaluating the partial image quality was proposed by Kuivalainen .The method results a binary mask which represents whether a certain location is applicablefor the analysis or not. DIARETDB0 includes a binary mask for every fundus image. The maskareas define where the distortion level caused by the imaging is sufficiently small, and onlyacceptableareasareusedintheevaluation.

Security

The patient information from the database imageswere removed by converting the imagesinto raw data. The raw data images were converted to lossless portable net- work images andmarkedtobelongDIARETDB0byredefiningthecommentfieldto"DIARETDB0imagefilename1500x1152DirectClassRGB".

Diabetes is primarily due to lifestyle factors and genetics. A number of lifestyle factors areknowntobeimportanttothedevelopmentoftype2diabetes,includingobesity(definedbya bodymassindex ofgreaterthan 30), lack of physical activity, poor diet, stress,and urbanization. Excess body fat is associated with 30% of cases in people of Chinese andJapanese descent, 60-80% of cases in those of European and African descent, and 100% ofPima Indians and Pacific Islanders. Even those who are not obese may have a high waist-hipratio.

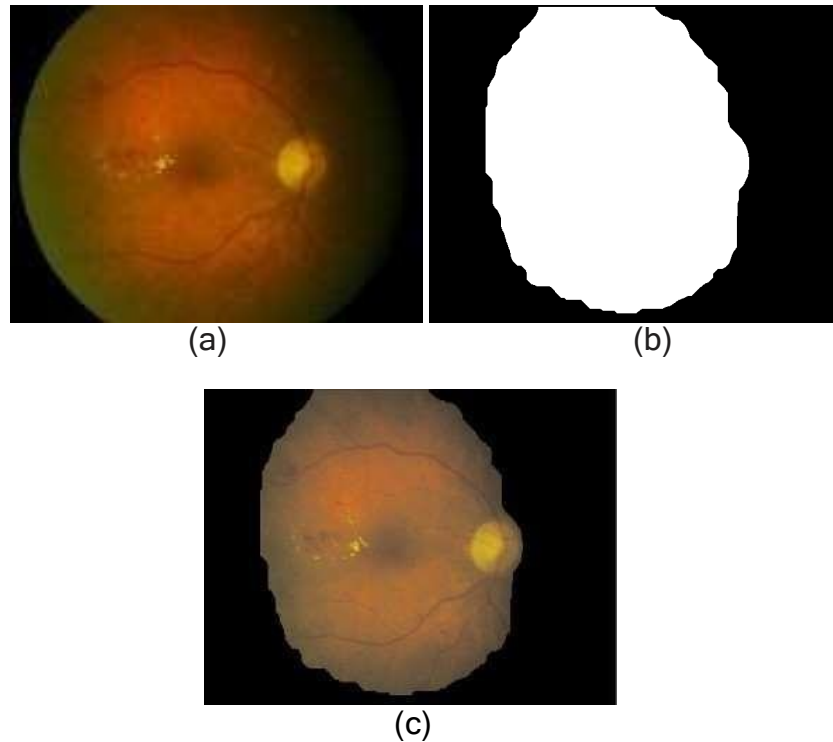


Figure 6: Image area with sufficient image quality: (a) original image; (b) binary mask; and (c) area used by the algorithms.

Training and test sets

The set of 130 images was divided into 5 image categories, and a fixed number of randomly selected images were taken from each category to form the training set. The rest of the images compose the test set. The image categories were formed to confirm that each diabetic retinopathy finding type is included in the both training and test sets. The diabetic retinopathy finding types that each image group contains are the following:

Red Small dots, haemorrhages, hard exudates.
 Red Small dots, haemorrhages, hard exudates, soft exudates.
 Red Small dots, haemorrhages, hard exudates, soft exudates,
 neovascularisation. Red small dots, haemorrhages, soft exudates, neovascularisation.
 Normal.

The categories represent the typical progress of the diabetic retinopathy [17].

Evaluation methodology for diabetic retinopathy

The proposed database and evaluation protocol are publicly available for all research groups who wish to evaluate their automatic diagnosis methods. By using the protocol and images defined in this document, the evaluation results are comparable between different studies.

Evaluation protocol

Methods used for automatic detection of diabetic retinopathy are evaluated by using sensitivity and specificity per image basis. Sensitivity is the percentage of abnormal funduses classified as abnormal by the screening method and specificity is the percentage of normal fundus classified as normal by the screening method. The higher the sensitivity and specificity values, the better the method. Sensitivity and specificity values are recalculated for three diabetic retinopathy finding classes: exudates (soft and hard), haemorrhages and red small dots (microaneurysm). In the current database the neovascularisation is not included due to its rarity.

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

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

P

where TP is the number of abnormal fundus images found as abnormal, T N is the number of normal fundus images found as normal, FP is the number of normal fundus images found as abnormal (false positives) and FN is the number of abnormal fundus images found as normal (false negatives).

For every image the area is given where the representative image quality is acceptable, and only the findings from those areas should be used. The results should be stored to a text file using the same structure as was defined for the ground truth files in the text files should be named as follows:

imagefilename.res, e.g., Image001.res

The provided evaluation script reads the result text files and calculates the sensitivity and specificity values over all images by comparing the results to the ground truth files.

Example on algorithm evaluation

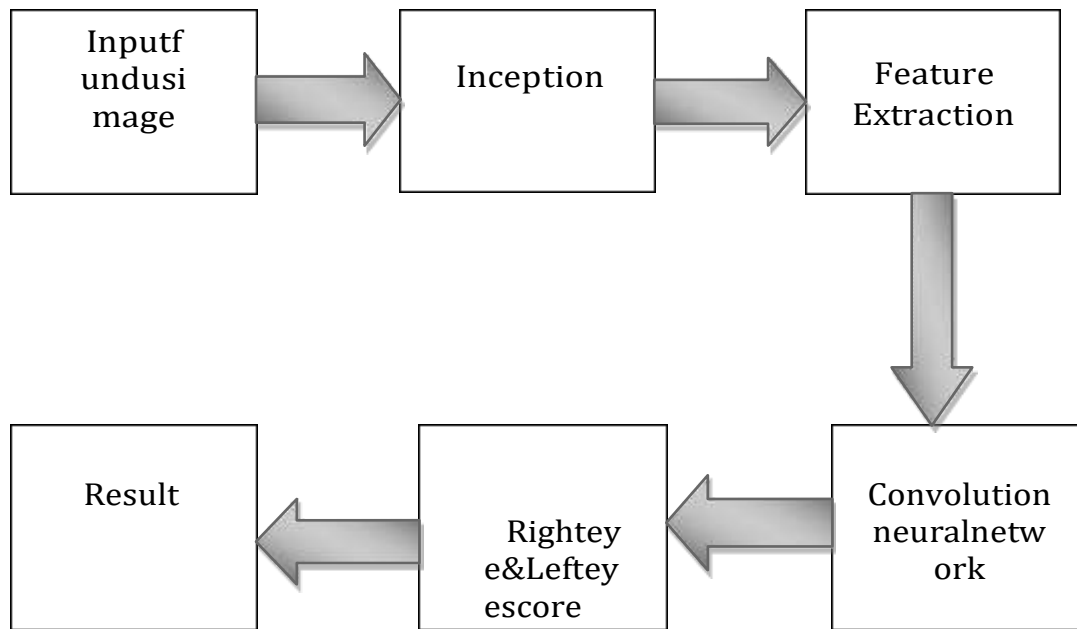
The method proposed by Kuivalainen was evaluated using the database and the evaluation methodology. It turned out, however, that the method could not be evaluated by the proposed evaluation protocol since the method assumed that the optic disk, papilla and blood vessels were perfectly detected and the findings from those areas were manually removed - an assumption which is very difficult to perform in practice, but which often appears in the studies. This is an example of "hidden" assumptions which actually prevent the true evaluation between the methods. Furthermore, it was only possible to evaluate the exudate detection which includes hard and soft exudates.

Evaluation result for the method

	Sensitivity%	Specificity%
Exudates	79	58

CHAPTER 4

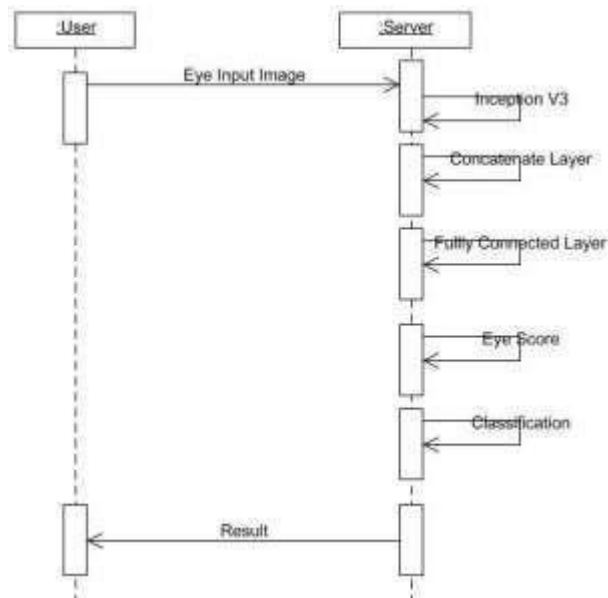
UML DIAGRAM



FigNo.4.1 Architecture of Automatic Diabetic Retinopathy Detection.

SequenceDiagram

A Sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of Message Sequence diagrams and is sometimes called event diagrams, event scenarios and timing diagrams.



FigNo.4.2SequenceDiagram.

UseCaseDiagram

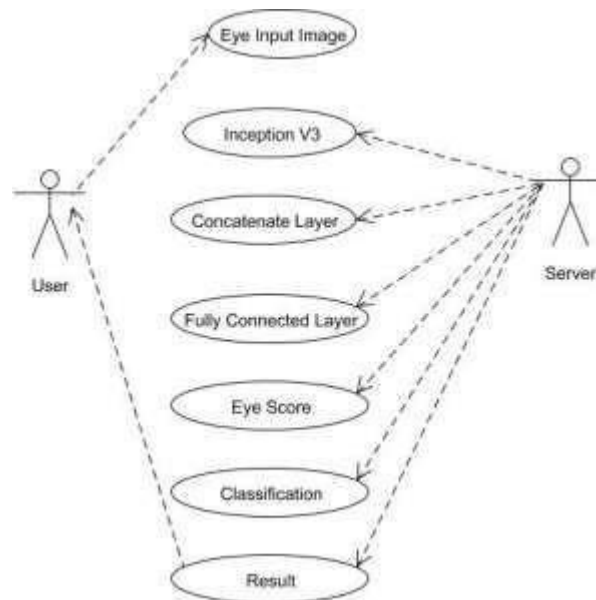
Unified Modeling Language (UML) is a standardized general-purpose modeling language in the field of software engineering. The standard is managed and was created by the Object Management Group. UML includes a set of graphic notation techniques to create visual models of software intensive systems. This language is used to specify, visualize, modify, construct and document the artifacts of an object oriented software intensive system under development.

USECASEDIAGRAM

A Use Case Diagram is used to present a graphical overview of the functionality provided by a system in terms of actors, their goals and any dependencies between those use cases. Use case diagram consists of two parts:

Use case: A use case describes a sequence of actions that provided something of measurable value to an actor and is drawn as a horizontal ellipse.

Actor: An actor is a person, organization or external system that plays a role in one or more interaction with the system.



FigNo.4.3 Use Case Diagram.

ActivityDiagram

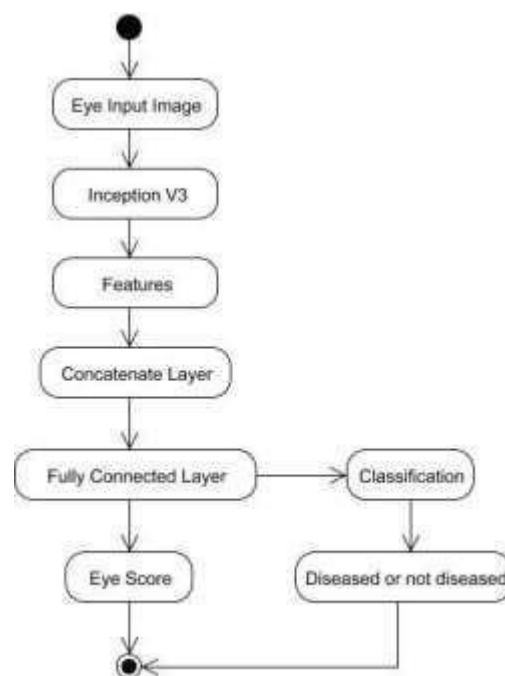
Activity diagram is a graphical representation of workflows of stepwise activities and actions with support for choice, iteration and concurrency. An activity diagram shows the overall flow of control.

The most important shapes types:

Rounded rectangles represent activities. Diamonds represent decisions.

Bars represent the start or end of concurrent activities. A black circle represents the start of the workflow.

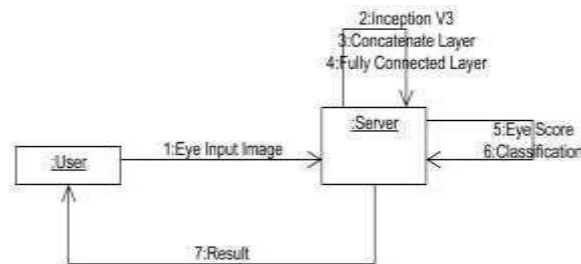
An encircled circle represents the end of the workflow.



FigNo.4.4ActivityDiagram.

CollaborationDiagram

UML Collaboration Diagrams illustrate the relationship and interaction between software objects. They require use cases, system operation contracts and domain model to already exist. The collaboration diagram illustrates messages being sent between classes and objects.



FigNo.4.5 Collaboration Diagram.

MODULES

MODULE EXPLANATION

- ImagePre-Processing
- Inception
- ConvolutionNeuralnetworkalgorithm
- MatchingScore

ImagePre-Processing

Dataset is a primary and significant part that needs to be dealt with for a deep learning application. The fundus photographs in our dataset have large variation, such as discrepant brightness or resolution, since most of them are obtained with different equipment in different environment. Basically, the model accepts two fundus images corresponding to the left eye and right eye as inputs and then transmits them into the Siamese-like blocks.

Inception

The outstanding performance of Inception is benefited by several network connection techniques, such as adopting batch normalization, using MLP conv layers to replace linear convolution layers and factorizing convolutions with large kernel size. With these techniques, the number of the network parameters as well as the computational complexity are reduced significantly, and thus the network can be built much deeper and get stronger non-linear expressive ability than that of the conventional CNN models.

Convolution Neural network algorithm

Transfer learning method is a widely used training method of convolution neural network. By loading the weights of Inception blocks pre-trained on Image Net data set, the model will have a better weight initialization before starting the gradient optimization. Moreover, considering the huge difference between the fundus images data set and Image Net dataset, none of the layers in weight-sharing Inception blocks are frozen.

Matching Score

The confusion matrices of prediction results of left eye, right eye, and both eyes together. The prediction results of the left eye and the right eye have very similar distribution patterns, indicating that the data partition method preserves the original image categories distribution of left eyes and right eyes.

CHAPTER 5 RESULTS AND DISCUSSION

Automated Per-Patient Screening

In the proposed screening scenario in which only patients who had not undergone photocoagulation treatment in either eye attended automated photographic screening, the automated lesion detection correctly identified 90.1% of the 129 patients with untreated diabetic retinopathy in either eye and 81.3% of the patients with no retinopathy. The overall accuracy was 86.8%. The proportion of false-negative grading (i.e., patients with retinopathy who were not identified by the algorithm) was 9.9%, whereas that of false-positive grading was 18.8%. All patients with false-negative grading had been reference-graded as having questionable retinopathy or minimal nonproliferative retinopathy with red lesions only.

The ROC demonstrated the range of options available in balancing the sensitivity and specificity of the algorithm. The area under the per-patient ROC curve was 93.6%.

Automated High-Sensitivity Per-Eye Grading

When compared with the expert reference grading, the automated analysis of the 260 color fundus photographs of nonphotocoagulated eyes correctly identified 93.1% of eyes with retinopathy and 71.6% of eyes without retinopathy. The overall accuracy was 83.5%. This result was achieved with the use of a lower visibility threshold (i.e., a higher lesion-detection sensitivity) than the default setting of the automated analysis system. The 10 eyes with false-negative identification had questionable or minimal nonproliferative retinopathy (eight eyes), hard exudates without the presence of red lesions (one eye), and proliferative diabetic retinopathy (one eye). The area under the per-eye ROC curve was 94.1%.

Routine Visual Per-Eye Grading

When comparing the routine visual grading of the 260 color fundus photographs of nonphotocoagulated eyes with the expert reference grading, the routine grading

correctly identified 76.4% of eyes with retinopathy and 98.3% of eyes without retinopathy. The overall accuracy was 86.2%. The proportion of false-negative classifications (i.e., eyes with retinopathy not identified by the routine grader) was 23.6%, whereas that of false-positives was 1.7%.

Automated High-Specificity Per-Eye Grading

When adjusting the visibility threshold to the value that most closely reproduced the sensitivity of the routine grader, the algorithm led to the correct identification of 76.4% of the eyes with diabetic retinopathy and 96.6% of the eyes without retinopathy. The overall accuracy was 85.4%. These results, as well as the proportions of false-positive (3.4%) and false-negative (23.6%) classifications, were not significantly different from those of the routine grader. The 34 false-negative eyes had questionable or minimal nonproliferative retinopathy (31 eyes), hard exudates without the presence of red lesions (one eye), and proliferative diabetic retinopathy (two eyes).

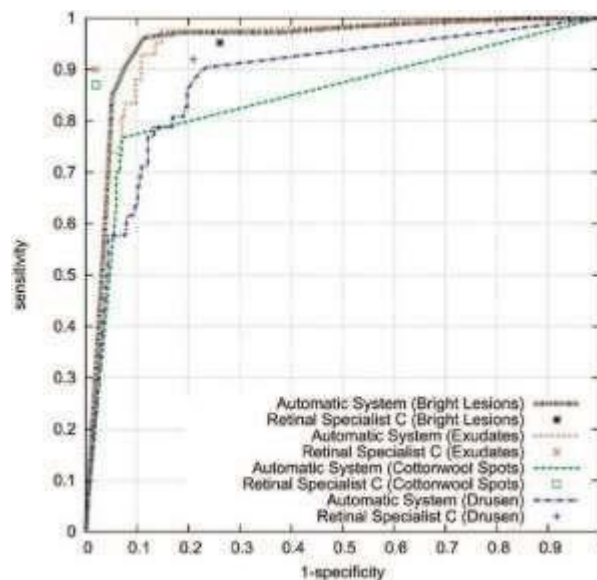


Fig.5.1: Automatic Detection of Diabetic Retinopathy.

Computer-Assisted Visual Per-Eye Grading

The automated high-sensitivity single-lesion detection was used in a visual regrading session in which the same routine grader examined the 260 fundus photographs on a computer display with mandatory consideration of the annotated image—that is, the digitized fundus image with overlaid lesion outlines in contrasting color. The grader was allowed to use image zooming and stretching facilities and to toggle lesion outlines off and on as needed. This resulted in correct identification of

% of eyes with retinopathy and 95.7% of eyes without retinopathy. The overall accuracy was 93.1%, a clear improvement over the performance of both routine visual grading and the automated system alone, with a proportion of false negatives of 9.0% and of false positive, 4.3%.

As in our previous study, 1 false-positive automatically detected lesions were found mainly in fundus regions with bright areas of nerve fiber striation interspersed with small vessel segments that were not identified as branches.

CHAPTER

6 CONCLUSION AND FUTURE WORK

The present study documented that computerized image analysis can achieve considerable effectiveness in distinguishing patients with diabetic retinopathy from patients without retinopathy. The sensitivity of the algorithm is adjustable, allowing for adaptation to specific screening protocols. At the default sensitivity setting, 73 of 81 patients (90.1%) with retinopathy were correctly identified by the algorithm in a population of patients with diabetes who had never undergone photocoagulation treatment. All patients with false-negative grading in this study had questionable retinopathy or minimal nonproliferative retinopathy with red lesions only. The potential risk of missing a diagnosis of such levels of retinopathy can be estimated on the basis of previous studies of the rate of progression of retinopathy. In the Early-Treatment Diabetic Retinopathy Study (ETDRS) the risk of progression to treatment requiring retinopathy over a 2-year period was below 1%.

The United Kingdom Prospective Diabetes Study (UKPDS) identified systemic parameters permitting stratification of patients with identical levels of retinopathy into subgroups with variable progression rates. Such information, if accessible in screening clinics, may enable a refined estimation of appropriate follow-up intervals for individual patients in retinopathy screening. This should minimize the concern that lesions in the far periphery, visible only by binocular contact lens biomicroscopic examination, are missed when only photographic methods are used for retinopathy screening. Ultimately, the choice of screening method must be based on an overall assessment of the options available in a given healthcare environment.

In the present study, we demonstrated the practicability of using automated digital detection of red lesions in photographic diabetic retinopathy screening. The objective was to sort patients who have not undergone photocoagulation treatment for diabetic retinopathy in two groups: those without retinopathy and those with possible or definite retinopathy who must have visual grading of their fundus photographs.

An automated prescreening system that automatically categorizes patients with diabetes into those who should have their photographs visually graded and those

whose photographs can reliably be handled automatically should be able to accomplish a series of functions. These include identification of images that are unsuitable for automated lesion detection (i.e., low-quality images caused by refractive media opacity or technical failures in the photographic process). Photographs with such characteristics should be automatically designated to visual inspection. Indeed, a preliminary evaluation of an automated quality-assessment algorithm developed subsequent to the completion of this study has demonstrated a significant potential for increasing the sensitivity of the automated classification by elimination of several of the false-negative gradings in this study, one of which had proliferative diabetic retinopathy. Additional enhancement appears to be possible by incorporating automated detection of bright fundus lesions. Thus, one eye with a false-negative grade had bright lesions only.

An ancillary finding was that the quality of high-volume visual routine grading was enhanced considerably when the attention of the routine grader was directed to potential fundus lesions by the automated lesion-detection system. This part of the study was appended after completion of the primary studies. The results should be considered indicative of a potential for methodological development, but the tentative conclusion should be verified in a larger prospective study.

Clinical ophthalmology emphasizes the detailed assessment of retinopathy at or above treatment thresholds. The task of making a fine distinction between presence and absence of any retinopathy is rarely addressed outside epidemiologic studies. Clinical ophthalmology practice is not traditionally subjected to validation or quality control, and it is therefore difficult to find standards against which new methods can be compared. Even when validation is attempted, there is usually no quality-assurance system in place to ensure the widespread application of certified standards of clinical ophthalmology. It appears that technological progress may enable application of such systems, even in complex clinical fields such as ophthalmology.

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APPENDICES A. SOURCE CODE

ECODE

```
import tensorflow as tf, sys

import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()

import argparse
import sys
import time

import numpy as np
import tensorflow as tf
import cv2
import os

os.listdir(r"E:/Python/Full/AutomatedDiabeticRetinopathyDetectionCNN/testing_images"
)

# Importing Keras libraries and
packages
from keras.models import Sequential
from keras.layers import Convolution2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers
import Dense
from keras.layers
import Dropout
from keras.layers.normalization import BatchNormalization

# Initializing the CNN classifier
classifier = Sequential()

# Convolution Step 1
classifier.add(Convolution2D(96, 11, strides = (4, 4), padding = 'valid',
```

```
input_shape=(224,224,3),activation ='relu'))
```

```
#MaxPoolingStep1
```

```
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding =  
'valid'))classifier.add(BatchNormalization())
```

```
# ConvolutionStep 2
```

```
classifier.add(Convolution2D(256, 11, strides = (1, 1), padding='valid', activation  
='relu'))
```

```
#MaxPoolingStep2
```

```
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2),  
padding='valid'))classifier.add(BatchNormalization())
```

```
# ConvolutionStep 3
```

```
classifier.add(Convolution2D(384,3,strides=(1,1),padding='valid',activation  
='relu'))classifier.add(BatchNormalization())
```

```
# ConvolutionStep 4
```

```
classifier.add(Convolution2D(384,3,strides=(1,1),padding='valid',activation  
='relu'))classifier.add(BatchNormalization())
```

```
# ConvolutionStep 5
```

```
classifier.add(Convolution2D(256,3,strides=(1,1),padding='valid',activation='relu'  
)
```

```
#MaxPoolingStep3
```

```
classifier.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding  
='valid'))classifier.add(BatchNormalization())
```

```
#
```

```
    Flatten
```

```
    GlobalMaxPooling2D
```

```
    Flatten
```

```
classifier.add(Flatten())
```

```
#FullConnectionStepclassifier.add(Dense(units=4096,activation='relu'))classifier.add(Dropo  
ut(0.4))classifier.add(BatchNormalization())
```

```

classifier.add(Dropout(0.4))classifier.add(Batch
Normalization())classifier.add(Dense(units=1
000,activation='relu'))classifier.add(Dropout(0.
2))classifier.add(BatchNormalization())classifi
er.add(Dense(units = 38, activation
='softmax'))classifier.summary()

```

```

#changethisasyouseefit#im

```

```

age_path= sys.argv[1]

```

```

image_path='testing_images/728_right.jpeg'

```

```

#Readintheimage_data

```

```

image_data=tf.gfile.FastGFile(image_path,'rb').read()

```

```

#

```

```

Loadslabelfile,stripsoffcarriagereturnla

```

```

bel_lines=[line.rstrip()forline

```

```

    intf.gfile.GFile("models/retrained_labels.txt")]

```

```

#Unpersistsgraphfromfile

```

```

withtf.gfile.FastGFile("models/retrained_graph.pb",'rb')

```

```

    asf:graph_def =

```

```

        tf.GraphDef()

```

```

    graph_def.ParseFromString(f.read())

```

```

    _=tf.import_graph_def(graph_def,name=")

```

```

withtf.Session()assess:

```

```

    #Feedtheimage_dataasinputtothegraphandgetfirstprediction

```

```

    softmax_tensor=sess.graph.get_tensor_by_name('final_res
ult:0')

```

```

    predictions=sess.run(softmax_tensor,\

```

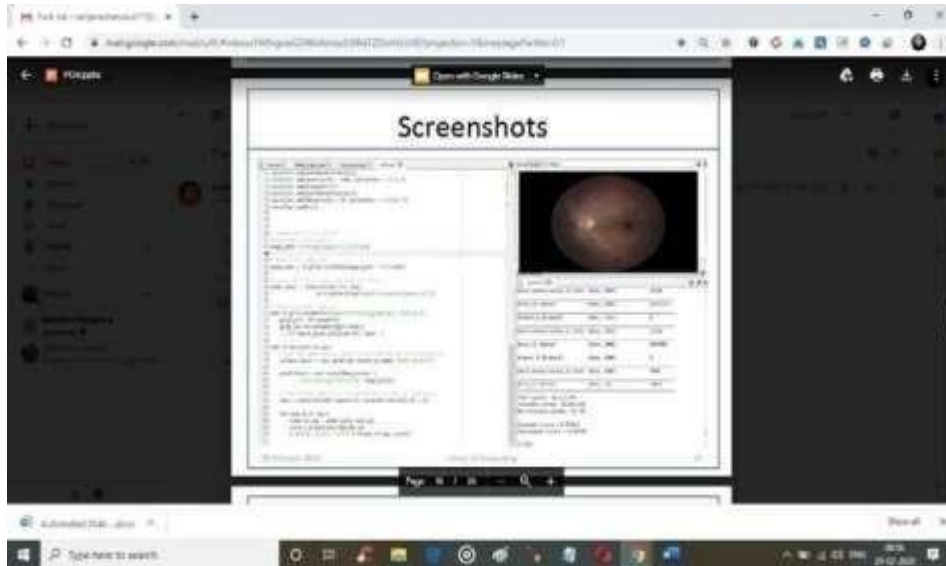
```

        {'DecodeJpeg/contents:0':image_data})

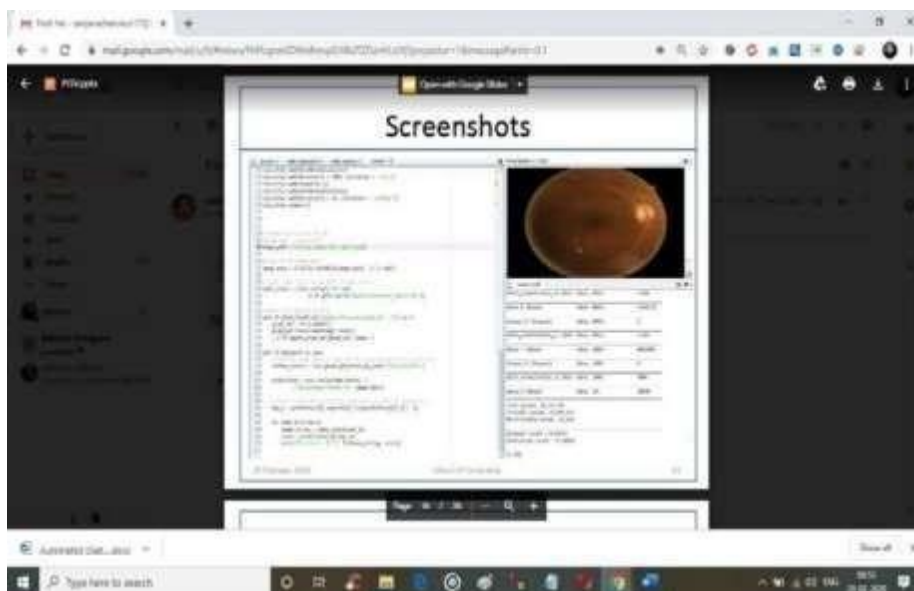
```

```
#Sort to show labels of first prediction in order of confidence
top_k=predictions[0].argsort()[-
len(predictions[0])::-1]
```

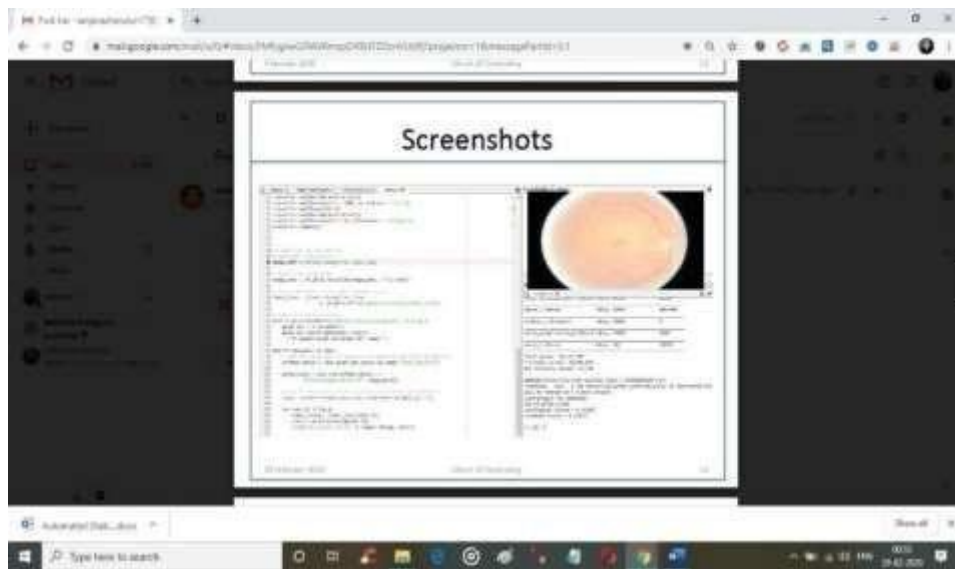
B.SCREENSHOTS



Imageswhiletesting



Testingprocessandvalues



Aftercompletediagnosis