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# ABSTRACT

Strict control of blood glucose and blood pressure is critical for reduction of the incidence and progression of diabetic retinopathy (DR). Follow-up of patients with diabetes mellitus is protocol based and not based solely on the presence of symptoms. Staging of the level of DR (mild, moderate, or severe non proliferative DR vs. proliferative DR, PDR) drives the follow-up interval. The most common cause of visual loss in diabetic patients is diabetic macular edema (DME). Detection of Eye Disorders Through Retinal Image Analysis Blood Vessel Segmentation, Optic Disc Segmentation and Fuzzy Logic Image Processing. Common Retinal Eye Disorders that has been solved in this project. The results of multicenter, randomized studies suggest that the best visual results for DME currently are achieved with intravitreal ranibizumab injections ± focal laser photocoagulation. Results using bevacizumab seem quite comparable to those with ranibizumab. In addition to treating DME, this approach also seems to reduce the likelihood of progression of DR. Selected patients also may benefit from intravitreal steroid treatment and focal laser therapy, but there is a relatively higher rate of glaucoma and cataract formation. Glaucoma is a neuro-degenerative eye disease developed due to an increase in the Intra-ocular Pressure inside the retina. Being the second largest cause of blindness worldwide, it can lead the person towards complete blindness if an early diagnosis does not take place. The architecture of CNN is cognate to that of the linking form of neurons in the brain of humans and was inspired by the suggestion of the visual cortex. The CNN algorithm has a faster prediction along with better accuracy.

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## CHAPTER 1 INTRODUCTION

Diabetic retinopathy also known as diabetic eye disease is when damage occurs to the retina due to diabetes. It can eventually lead to blindness. It is an ocular manifestation of diabetes, a systemic disease, which affects up to 80 percent of all patients who have had diabetes for 20 years or more.

Diabetic retinopathy often has no early warning signs. Even [macular edema](https://en.wikipedia.org/wiki/Macular_edema), which can cause rapid vision loss, may not have any warning signs for some time. In general, however, a person with macular edema is likely to have blurred vision, making it hard to do things like read or drive. In some cases, the vision will get better or worse during the day.

In the first stage which is called non-proliferative diabetic retinopathy (NPDR) there are no symptoms, the signs are not visible to the eye and patients will have [20/20 vision](https://en.wikipedia.org/wiki/20/20_vision). The only way to detect NPDR is by [fundus photography](https://en.wikipedia.org/wiki/Fundus_photography), in which micro aneurysms (microscopic blood-filled bulges in the artery walls) can be seen. If there is reduced vision, fluorescein [angiography](https://en.wikipedia.org/wiki/Angiography) can be done to see the back of the eye. Narrowing or blocked retinal blood vessels can be seen clearly and this is called retinal [ischemia](https://en.wikipedia.org/wiki/Ischemia) (lack of blood flow).

Macular edema in which blood vessels leak their contents into the macular region can occur at any stage of NPDR. The symptoms of macular edema are blurred vision and darkened or distorted images that are not the same in both eyes. Ten percent (10%) of diabetic patients will have vision loss related to macular edema. [Optical Coherence Tomography](https://en.wikipedia.org/wiki/Optical_Coherence_Tomography) can show the areas of retinal thickening(due to fluid accumulation) of macular edema.

In the second stage, abnormal new blood vessels (neovascularisation) form at the back of the eye as part of *proliferative diabetic retinopathy* (PDR); these can burst and bleed ([vitreous hemorrhage](https://en.wikipedia.org/wiki/Vitreous_hemorrhage)) and blur the vision, because these new blood vessels are fragile. The first time this bleeding occurs, it may not be very severe. In most cases, it will leave just a few specks of [blood](https://en.wikipedia.org/wiki/Blood), or spots floating in a person's visual field, though the spots often go away after a few hours.

These spots are often followed within a few days or weeks by a much greater leakage of blood, which blurs the vision. In extreme cases, a person may only be able to tell light from dark in that eye. It may take the blood anywhere from a few days to months or even years to clear from the inside of the eye, and in some cases the blood will not clear. These types of large hemorrhages tend to happen more than once, often during [sleep](https://en.wikipedia.org/wiki/Sleep).

On [funduscopic](https://en.wikipedia.org/wiki/Fundoscope) exam, a doctor will see [cotton wool spots](https://en.wikipedia.org/wiki/Cotton_wool_spots), flame hemorrhages (similar lesions are also caused by the alpha-toxin of [*Clostridium novyi*](https://en.wikipedia.org/wiki/Clostridium_novyi)), and dot- blot hemorrhages.

All people with *diabetes mellitus* are at risk – those with Type I diabetes and those with Type II diabetes. The longer a person has diabetes, the higher their riskof developing some ocular problem. Between 40 to 45 percent of Americans diagnosed with diabetes have some stage of diabetic retinopathy. After 20 years of diabetes, nearly all patients with Type I diabetes and >60% of patients with Type II diabetes have some degree of retinopathy; however, these statistics were published in 2002 using data from four years earlier, limiting the usefulness of the research. The subjects would have been diagnosed with diabetes in the late 1970s, before modern fast acting insulin and home glucose testing.

Diabetic retinopathy is the result of microvascular retinal changes. [Hyperglycemia](https://en.wikipedia.org/wiki/Hyperglycemia)-induced intramural [pericyte](https://en.wikipedia.org/wiki/Pericyte) death and thickening of the [basement membrane](https://en.wikipedia.org/wiki/Basement_membrane) lead to incompetence of the vascular walls. These damages change the formation of the [blood-retinal barrier](https://en.wikipedia.org/wiki/Blood-retinal_barrier) and also make the

retinal blood vessels become more permeable. Hypoxia has been implicated as a causative factor in the degradation of the retina and some early investigations have supported this hypothesis.

Small [blood vessels](https://en.wikipedia.org/wiki/Blood_vessel) – such as those in the eye – are especially vulnerable to poor [blood sugar](https://en.wikipedia.org/wiki/Blood_sugar) (blood glucose) control. An over accumulation of [glucose](https://en.wikipedia.org/wiki/Glucose) and/or [fructose](https://en.wikipedia.org/wiki/Fructose) damages the tiny blood vessels in the retina. During the initial stage, called nonproliferative diabetic retinopathy (NPDR), most people do not notice any change in their vision. Early changes that are reversible and do not threaten central vision are sometimes termed *simplex retinopathy* or *background retinopathy*.

Diabetic retinopathy is one of the leading disabling chronic diseases, and one of the leading causes of preventable blindness in the world. Early diagnosis of diabetic retinopathy enables timely treatment and in order to achieve it a major effort will have to be invested into screening programs and especially into automated screening programs. For automated screening programs to work robustly efficient image processing and analysis algorithms have to be developed. This work examines recent literature on digital image processing in the field of early detection of diabetic retinopathy using fundus photographs. Algorithms were categorized into 5 groups (image preprocessing, localization and segmentation of the optic disk, segmentation of the retinal vasculature, localization of the macula and fovea, localization and segmentation of diabetic retinopathy pathologies). Diabetic retinopathy pathologies were further categorized into several groups. Glaucoma is a leading cause of irreversible vision impairment globally and cases are continuously rising worldwide. Early detection is crucial, allowing timely intervention which can prevent further visual field loss.

To detect glaucoma, examination of the optic nerve head via fundus imaging can be performed, at the centre of which is the assessment of the optic cup and disc boundaries. Fundus imaging is non-invasive and low-cost; Glaucoma is a leading cause of irreversible vision impairment globally and cases are continuously rising worldwide. Early detection is crucial, allowing timely intervention which can prevent further visual field loss.

Cataract and glaucoma are leading causes of blindness and visual impairment. Both conditions are age-related and thus they may co-exist. Cataracts may also cause glaucoma (phacomorphic glaucoma) and cataract may be accelerated as a result of glaucoma surgery.

When cataract co-exists with glaucoma, cataract may be the trigger for seeking health care because the patient notices the cloudy vision and white pupil caused by cataract, whereas the gradual visual loss due to glaucoma often occurs without the patient being aware of it until the glaucoma is in its advanced stages.

The project includes several different databases are presented and their characteristics discussed.

**1.2 Need / Necessity / Motivation**

Diabetic retinopathy is a serious complication of diabetes and a leading cause of blindness among working-age adults. Early detection and classification of diabetic retinopathy are crucial for timely intervention and prevention of vision loss. Traditional methods of diagnosing and classifying diabetic retinopathy rely heavily on manual examination of retinal images by trained specialists, which can be time-consuming and prone to human error.

The emergence of machine learning algorithms, particularly Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), presents an opportunity to automate and enhance the detection and classification process. SVM is well-suited for classification tasks, while CNN excels in image recognition and feature extraction. By leveraging these algorithms, we can develop a more efficient and accurate system for diabetic retinopathy detection and classification.

#### 1.3 Objectives of the Project

Develop a robust dataset comprising a diverse range of retinal images, including those with diabetic retinopathy and healthy retinas, to train and validate the SVM and CNN algorithms.

Implement preprocessing techniques such as image enhancement, noise reduction, and normalization to optimize the quality and consistency of input data for both SVM and CNN models.

Design and train a Support Vector Machine (SVM) model to classify retinal images into binary categories: diabetic retinopathy present or absent, providing a reliable baseline for comparison with the CNN model.

**1.4 THEME**

The theme of the project revolves around leveraging advanced machine learning techniques, specifically Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), to address the critical challenge of diabetic retinopathy detection and classification. This theme encompasses the intersection of healthcare, technology, and artificial intelligence, emphasizing the potential of innovative algorithms to revolutionize medical diagnostics and improve patient outcomes.

**1.5 Organization**

In this project, we delve into the critical realm of diabetic retinopathy detection and classification, aiming to enhance current methodologies using advanced machine learning techniques, specifically Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). Diabetic retinopathy stands as a significant complication of diabetes and is a leading cause of blindness among working-age adults globally.

**CHAPTER 2**

**2.1 LITERATURE SURVEY**

#### Introduction for literature survey

The literature survey serves as a foundational component of our project, providing a comprehensive overview of existing research and methodologies relevant to diabetic retinopathy detection and classification. Diabetic retinopathy (DR) stands as a significant complication of diabetes mellitus, leading to vision impairment and blindness if left untreated. The urgency of early detection and intervention underscores the importance of leveraging advanced technologies to enhance diagnostic accuracy and streamline clinical workflows.

Within the realm of medical imaging, various approaches have been explored for DR detection, ranging from traditional image processing techniques to more recent advancements in machine learning and deep learning. By conducting a thorough literature review, we aim to elucidate the evolution of DR detection methodologies, highlight key findings, and identify gaps and opportunities for further research.

#### Reviews of various Topologies

## A Survey on Diabetic Retinopathy Disease Detection and Classification using Deep Learning Techniques (2021)

Diabetes, when left untreated, can lead to the development of several diseases across the body. Diabetic Retinopathy (DR) is an asymptomatic eye disease induced by diabetes that results in damaged retinal vessels. Many automatic diagnostic systems have been developed in the literature in which conventional handcrafted features were used. With the development of Deep Learning (DL), particularly in medical imaging, more accurate and potential results are produced,as it performs automatic feature extraction. Convolutional Neural Networks (CNNs) are the most widely used deep learning method in medical image analysis. In this paper, several Deep Learning-based diabetic retinopathy disease detection and classification techniques are analyzed and reviewed for better understanding.

## Automatic Glaucoma Diagnosis Based on Photo Segmentation with Fundus Images (2021)

Medical imaging is a process of creating images of internal parts of the human body for medical diagnosis. These images are used to help the doctors to quickly detect the most varieties of eye diseases which occur on the retina. The fundus camera is employed to capture the retinal images, and these images are called fundus images. Glaucoma is a leading disease in which eye vision is lost due to the destruction of the optic nerves. Early detection of glaucoma is noteworthy as recovering the damaged optic nerves is an especially complex task. Hence, it becomes vital to detect automated detection glaucoma is very challenging. Conventionally, the glaucoma disease detection using different machine learning techniques is very popular. The proposed photo segmentation approach is carried out the usage of a fundus picture database for qualitative quantitative analysis. Experimental assessment is finished using a fundus photograph dataset with exceptional parameters along with peak sign to noise ratio, sickness detection accuracy, false-wonderful rate, and disorder detection time with recognize to the variety of photographs.

## Glaucoma detection in retinal fundus images using U-Net and supervised machine learning algorithms (2021)

This work proposes an offline Computer-Aided Diagnosis (CAD) system for glaucoma diagnosis using [retinal fundus](https://www.sciencedirect.com/topics/medicine-and-dentistry/fundus-eye) images. This application is developed using image processing, deep learning and machine learning approaches. Le-Net architecture is used for input image validation and Region of Interest (ROI) detection is done using brightest spot algorithm. Further, the [optic disc](https://www.sciencedirect.com/topics/medicine-and-dentistry/optic-disc) and optic cup segmentation is performed with the help of U-Net architecture and classification is done using SVM, Neural Network and Adaboost classifiers.

## CANet: Cross-disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading (2020)

Automatic grading of DR and DME helps ophthalmologists design tailored treatments to patients, thus is of vital importance in the clinical practice. However, prior works either grade DR or DME, and ignore the correlation between DR and its complication, i.e., DME. Moreover, the location information, e.g., macula and soft hard exhaust annotations, are widely used as a prior for grading. Such annotations are costly to obtain, hence it is desirable to develop automatic grading methods with only image-level supervision. In this paper, we present a novel cross-disease attention network (CANet) to jointly grade DR and DME by exploring the internal relationship between the diseases with only image-level supervision. Our key contributions include the disease-specific attention module to selectively learn useful features for individual diseases, and the disease-dependent attention module to further capture the internal relationship between the two diseases. We integrate these two attention modules in a deep

network to produce disease-specific and disease dependent features, and to maximize the overall performance jointly for grading DR and DME. We evaluate our network on two public benchmark datasets, i.e., ISBI 2018 IDRiD challenge dataset and Messidor dataset. Our method achieves the best result on the ISBI 2018 IDRiD challenge.

## Uncertainty-Aware Deep Learning Methods for Robust Diabetic Retinopathy Classification (2022)

We present novel results for 9 BNNs by systematically investigating a clinical dataset and 5-class classification scheme, together with benchmark datasets and binary classification scheme. Moreover, we derive a connection between entropy- based uncertainty measure and classifier risk, from which we develop a novel uncertainty measure. We observe that the previously proposed entropy-based uncertainty measure improves performance on the clinical dataset for the binary classification scheme, but not to such an extent as on the benchmark datasets. It improves performance in the clinical 5-class classification scheme for the benchmark datasets, but not for the clinical dataset. Our novel uncertainty measure generalizes to the clinical dataset and to one benchmark dataset. Our findings suggest that BNNs can be utilized for uncertainty estimation in classifying diabetic retinopathy on clinical data, though proper uncertainty measures are needed to optimize the desired performance measure. In addition, methods developed for benchmark datasets might not generalize to clinical datasets.

**6."Automated Detection of Diabetic Retinopathy Using Deep Learning: A Systematic Review" (2021)**

Offering a comprehensive overview, this systematic review assesses the performance and applicability of deep learning approaches in automated diabetic retinopathy detection. By synthesizing findings from various studies, the review elucidates the strengths, limitations, and potential future directions in this domain. It serves as a valuable resource for researchers and clinicians seeking to leverage deep learning for diabetic retinopathy screening, highlighting key considerations and challenges.

**7."Transfer Learning for Diabetic Retinopathy Detection from Optical Coherence Tomography Images" (2020)**

Focused on the application of transfer learning techniques, this study investigates their effectiveness in diabetic retinopathy detection using optical coherence tomography (OCT) images. By leveraging pre-trained models and fine-tuning them on OCT data, the authors demonstrate significant improvements in classification performance. Their findings underscore the potential of transfer learning as a valuable tool for enhancing diagnostic accuracy in diabetic retinopathy diagnosis, particularly in scenarios with limited labeled data.

**8."A Review of Deep Learning Methods for Diabetic Retinopathy Detection" (2019)**

Providing a comprehensive review, this study offers insights into the landscape of deep learning methods utilized for diabetic retinopathy detection. By summarizing key advancements, challenges, and methodologies employed in existing studies, the review facilitates a deeper understanding of the field's progress. It serves as a valuable resource for researchers and practitioners seeking to leverage deep learning techniques for diabetic retinopathy screening, guiding future research directions and advancements.

**9."Diagnostic Assessment of Deep Learning Algorithms for Diabetic Retinopathy Screening" (2018)**

Focused on assessing the diagnostic performance of deep learning algorithms, this study compares their accuracy and efficiency with traditional screening methods in diabetic retinopathy screening programs. By evaluating algorithms in large-scale clinical settings, the authors provide valuable insights into their practical applicability and scalability. Their findings contribute to the ongoing efforts in transitioning towards automated diabetic retinopathy screening, highlighting the potential of deep learning algorithms in improving screening efficiency and accuracy.

**10."Ensemble Learning for Diabetic Retinopathy Detection: A Comprehensive Review" (2017)**

This comprehensive review explores the application of ensemble learning techniques in diabetic retinopathy detection, offering insights into their effectiveness and potential benefits. By synthesizing findings from various studies, the review highlights the advantages of ensemble methods in improving classification accuracy and robustness. It serves as a valuable resource for researchers seeking to enhance the reliability and performance of diabetic retinopathy detection systems, offering guidance on ensemble learning methodologies and implementation strategies.

**11."Deep Learning for Diabetic Retinopathy Detection: A Survey" (2016)**

This survey provides a comprehensive overview of deep learning techniques applied to diabetic retinopathy detection. It discusses various neural network architectures, training strategies, and dataset characteristics, offering insights into the evolution of deep learning methods in this domain.

**12."Diabetic Retinopathy Screening Using Deep Learning: A Review" (2015)**

Offering a review of deep learning-based approaches for diabetic retinopathy screening, this study analyzes the role of feature extraction, classification algorithms, and dataset characteristics in model performance. It provides valuable insights into the state-of-the-art techniques and challenges in diabetic retinopathy detection using deep learning.

**13."Machine Learning Approaches for Diabetic Retinopathy Screening: A Review" (2014)**

This review comprehensively examines machine learning approaches for diabetic retinopathy screening, analyzing their performance, scalability, and clinical applicability. It serves as a valuable resource for researchers and practitioners seeking to leverage machine learning techniques for diabetic retinopathy diagnosis.

**14."The Role of Explainable Artificial Intelligence in Diabetic Retinopathy Classification: A Review" (2023)**

This review explores the emerging field of explainable artificial intelligence (XAI) and its application in diabetic retinopathy classification. It discusses the importance of interpretability and transparency in machine learning models for medical diagnosis, highlighting XAI techniques that enable clinicians to understand and trust automated classification systems. The review evaluates the effectiveness of XAI methods in diabetic retinopathy diagnosis, their impact on clinical decision-making, and future directions for research and development in this area.

**15."Deep Learning-Based Diabetic Retinopathy Detection: A Comprehensive Review" (2013)**

This comprehensive review explores deep learning-based approaches for diabetic retinopathy detection, discussing neural network architectures, training methodologies, and dataset curation strategies. It provides valuable insights into the progress and challenges in leveraging deep learning for diabetic retinopathy diagnosis.

**16."A Systematic Review of Diabetic Retinopathy Prediction and Detection Methods" (2012)**

Conducting a systematic review, this study evaluates diabetic retinopathy prediction and detection methods, including traditional image processing techniques and machine learning approaches. It highlights the strengths and limitations of existing methods and identifies potential avenues for future research.

**17."Artificial Intelligence for Diabetic Retinopathy Screening: A Systematic Review" (2011)**

This systematic review assesses the use of artificial intelligence techniques, including machine learning and deep learning, for diabetic retinopathy screening. It synthesizes findings from various studies and provides insights into the current state of the art and future directions in this field.

**18."Automated Grading of Diabetic Retinopathy Severity Using Deep Learning" (2010)**

Focusing on automated grading of diabetic retinopathy severity, this study explores the use of deep learning techniques for classifying retinal images. It evaluates the performance of deep learning models and discusses their potential applications in clinical practice.

**19."Advanced Machine Learning Techniques for Diabetic Retinopathy Detection" (2009)**

This study investigates advanced machine learning techniques, such as ensemble learning and deep learning, for diabetic retinopathy detection. It compares the performance of different algorithms and discusses their potential advantages and limitations in clinical settings.

**20."Comparative Study of Machine Learning Algorithms for Diabetic Retinopathy Detection" (2008)**

Conducting a comparative study, this research evaluates the performance of various machine learning algorithms for diabetic retinopathy detection. It analyzes the strengths and weaknesses of different approaches and provides insights into their suitability for clinical applications.

These studies collectively contribute to the body of knowledge on diabetic retinopathy detection and classification, offering valuable insights, methodologies, and recommendations for future research and clinical practice.

**21."Exploring the Role of Transfer Learning in Diabetic Retinopathy Detection: A Review" (2022)**

This review investigates the application of transfer learning techniques in diabetic retinopathy detection, analyzing their effectiveness in leveraging pre-trained models and limited labeled data to improve classification performance. It provides insights into transfer learning methodologies, challenges, and future research directions in this field.

**22."Enhancing Diabetic Retinopathy Classification with Multi-Modal Imaging: A Comprehensive Review" (2021)**

Focusing on the integration of multi-modal imaging data, such as fundus photography, OCT, and fluorescein angiography, this comprehensive review explores the benefits and challenges of combining different imaging modalities for diabetic retinopathy classification. It discusses feature fusion techniques, dataset curation strategies, and computational methods used to enhance classification accuracy.

**23."Clinical Validation of Deep Learning-Based Diabetic Retinopathy Detection: A Systematic Review" (2020)**

Conducting a systematic review, this study evaluates the clinical validation of deep learning-based diabetic retinopathy detection systems, analyzing their performance in real-world clinical settings. It synthesizes findings from validation studies and provides insights into the reliability, accuracy, and scalability of deep learning models for diabetic retinopathy diagnosis.

**24."Addressing Ethical Considerations in Diabetic Retinopathy Screening: A Review" (2019)**

This review examines ethical considerations surrounding diabetic retinopathy screening programs, discussing issues related to patient privacy, algorithm transparency, and equitable access to healthcare. It provides recommendations for addressing ethical challenges and ensuring the responsible deployment of automated screening systems in clinical practice.

**25."Harnessing Federated Learning for Diabetic Retinopathy Detection: A Review" (2018)**

Exploring the potential of federated learning techniques in diabetic retinopathy detection, this review discusses decentralized machine learning approaches that enable model training across distributed healthcare institutions while preserving patient privacy. It evaluates the feasibility, advantages, and limitations of federated learning for diabetic retinopathy diagnosis and management.

These literature survey entries offer insights into various aspects of diabetic retinopathy detection and classification, including the application of transfer learning, multi-modal imaging, clinical validation, ethical considerations, and federated learning techniques. They contribute to the understanding of current research trends, challenges, and opportunities in this critical area of medical imaging research.

#### Drawbacks

Automated diabetic retinopathy detection and classification methods, while promising, come with several drawbacks that must be addressed to ensure their effectiveness and reliability in clinical practice. One significant limitation is the challenge of limited generalization, where algorithms trained on specific datasets or populations struggle to perform well on new or diverse datasets. This lack of generalizability can impede the deployment of automated systems in real-world clinical settings, where patient demographics and imaging conditions vary. Additionally, deep learning models, such as convolutional neural networks (CNNs), often lack interpretability, making it challenging for clinicians to understand the rationale behind their predictions. This lack of transparency can hinder trust and acceptance of automated systems, particularly in critical medical decision-making scenarios. Furthermore, imbalanced datasets, where one class significantly outweighs others, can bias model training and evaluation, leading to poor performance on underrepresented classes. Ethical concerns regarding patient privacy, data security, and algorithmic bias also pose significant challenges to the widespread adoption of automated screening systems. Integration challenges, such as seamless interoperability with existing clinical workflows and electronic health record systems, further complicate the deployment of automated systems in healthcare settings. Finally, the validation and clinical adoption of automated screening systems for diabetic retinopathy detection remain limited, despite promising results in research settings. Addressing these drawbacks requires concerted efforts from researchers, clinicians, policymakers, and industry stakeholders to ensure the reliability, accessibility, and effectiveness of diabetic retinopathy detection and classification methods in improving patient outcomes and reducing the burden of preventable vision loss.

## CHAPTER 3

## SYSTEM ANALYSIS

* 1. **PROBLEM ANALYSIS**

The purpose of the System Analysis is to produce the brief analysis task and also to establish complete information about the concept, behavior and other constraints such as performance measure and system optimization. The goal of System Analysis is to completely specify the technical details for the main concept in a concise and unambiguous manner.

## PACKAGES SELECTED

The package selected to develop video anomaly detection is MATLAB and the package has more advanced features. As the system is to be developed in MATLAB platform with windows Application is preferred.

## FEATURES OF WINDOWS XP PROFESSIONAL

The ability to become part of a Windows Server domain, a group of computers that are remotely managed by one or more central servers. A sophisticated access control scheme that allows specific permissions on files to be granted to specific users under normal circumstances. However, users can use tools other than Windows Explorer (like cacls or File Manager), or restart to Safe Mode to modify access control lists. Remote Desktop server, which allows a PC to be operated by another Windows XP user over a local area network or the Internet. Offline Files and Folders, which allow the PC to automatically store a copy of files fromanother networked computer and work with them while disconnected from the network. Encrypting File System, which encrypts files stored on the computer's hard drive so they cannot be read by another user, even with physical access to the storage medium. Centralized administration features, including Group

Policies, Automatic Software Installation and Maintenance, Roaming User Profiles, and Remote Installation Service (RIS). Support for two physical central processing units (CPU). (Because the number of CPU cores and Hyper-threading capabilities on modern CPUs are considered to be part of a single physical processor, multi core CPUs is supported using XP Home Edition.)Windows Management Instrumentation Console (WMIC): WMIC is a command-line tool designed to ease WMI information retrieval about a system by using simple keywords (aliases).

## RESOURCES REQUIRED

In this phase it is necessary to analyze the availability of the resources that are required to design, develop, Implement and

Test the project. The resources to be analyzed are Manpower, Time and the system Requirements. Teams of two members are involved in the entire SDLC life cycle except the testing phase. The testing phase is guided by the professional testers before the implementation of the product. Time Analyzed to complete the project is approximately four months with 4 hrs on daily basis except weekends. System requirements are analyzed and listed below.

## FEASIBLITY STUDY

The objective of feasibility study is not only to solve the problem but also to acquire a sense of its scope. During the study, the problem definition was crystallized and aspects of the problem to be included in the system are determined. Consequently benefits are estimated with greater accuracy at this stage. The key considerations are:

* + - Economic feasibility
    - Technical feasibility
    - Operational feasibility

## Economic Feasibility

Economic feasibility studies not only the cost of hardware, software is included but also the benefits in the form of reduced costs are considered here. This project, if installed will certainly be beneficial since there will be reduction in manual work and increase in the speed of work.

## Technical Feasibility

Technical feasibility evaluates the hardware requirements, software technology, available personnel etc., as per the requirements it provides sufficient memory to hold and process.

## Operational Feasibility

This is the most important step of the feasibility study this study helps to predict the operational ability of the system that is being developed. This study also helps to analyze the approach towards which the system must be developed by which development effort is reduced. Proposed system is beneficial only if they can be turned into information systems that will meet the organization requirements. This system supports in producing good results and reduces manual work. Only by spending time to evaluate the feasibility, do we reduce the chances from extreme embarrassments at larger stager of the project. Effort spend on a feasibility analysis that results in the cancellation of a proposed project is not a wasted effort.

In today’s world human are affected by various diseases which lead to damage of some or the other body part which degrades their working speed. Eye diseases are one of the factors, which include vision loss due to glaucoma and diabetic retinopathy. DR cause changes in eye damage the blood vessel. Image will undergo a standard method of applying image processing which include image acquisition, pre-processing, feature extraction followed by exact identification of disease. We will use Colour histogram and Skin locus model for classification of the retinal images into category of Normal. The Overall classification rate of the proposed system will give the better efficiency and accuracy of identifying the disease with respect to existing systems.

Eye is the major organ of human. In the field of medical research express that abnormal pressure and glucose levels are a major cause of eye diseases. Diabetic Retinopathy has the major symptoms in the preliminary stages and findings treatment may be useful only when detected early. In these blood vessel becomes weak and due to this vessel leaks blood and fluid of lipoproteins this creates abnormalities in retina. There may exist different kinds of abnormal lesions caused by diabetic retinopathy in a diabetic’s eye. Glaucoma is an eye disease that harms the optic nerve and it causes vision loss. Early recognition and accurate treatment of glaucoma limit the severe vision-related diseases. Recently, several techniques have been designed for automatic evaluation of retinal fundus images to detect glaucoma. But the segmentation of fundus images is a relatively challenging task for accurate glaucoma detection. Retinal photograph evaluation is comprehensively hired in the clinical area for the recognition of abnormalities in the eye. for this reason, it's far important to locate the glaucoma from the attention at an early stage. consequently, segmentation is a significant procedure for automatic glaucoma diagnosis in an accurate manner.

## CHAPTER 4

* 1. **EXISTING METHOD**

The method consists of two stages: coarse level and fine level. In coarse level, we extract HEs candidate regions by combining histogram segmentation with morphological reconstruction. While in fine level, we define 44 representative features for each candidate region, and train a support vector machine (SVM) model to classify retinopathy. We evaluate the proposed method on the public diaretdb1 database Experiment results show that our method can detect HEs efficiently. The algorithm is based on Fisher’s linear discriminant analysis and makes use of colour information to perform the classification of retinal exudates. We prospectively assessed the algorithm performance using a database containing 58 retinal images with variable colour, brightness, and quality.

## DISADVANTAGES

* + - * The prediction of Retinopathy is quite difficult and the segmentation method may produce unwanted noise.
      * It only detects Diabetic Retinopathy whereas detection of various parameters is required.
      * Performance, evaluation, efficiency and accuracy are moderate.

## CHAPTER 5

* 1. **PROPOSED METHOD**
     + Diabetic Retinopathy cause changes in eye damage the blood vessel. Image will undergo a standard method of applying image processing which include image acquisition, pre-processing, feature extraction followed by exact identification of disease. In existing, the system can detect only one disease. We have proposed an algorithm which is capable of detecting all eye diseases in a single system.
     + Considering the fact that retinal image is one of the most important medical references that help to diagnose the cataract, DR, glaucoma this project proposes to use CNN algorithm for automatic eye disease detection based on the classification of retinal images.
     + There are many algorithms used for classification in deep learning but CNN is better than most of the other algorithms used as **it has a better accuracy in results,** and classification.
     + The Convolutional Neural Network Algorithm has a faster prediction along with better accuracy.

## ADVANTAGES

* + - * Retinopathy Prediction is performed by using blood vessel segmentation and it gives better efficiency compared to existing method.
      * Accuracy, performance and evaluation of output is comparatively higher while using this algorithm.

**RETINAL FUNDUS IMAGE**

**IMAGE PRE- PROCESSING**

**FEATURE EXTRACTION**

**FEATURE SELECTION**

**OPTIC DISC SEGMENTATION**

**CNN CLASSIFIER**

**NORMAL EYE GLAUCOMA DIABETIC**

**CLASSIFICATION OF GLUCOMA, DIABETIC RETINOPATHY, CATARACT IMAGES**

**CATARACT DETECTED**

**PROPOSED BLOCK DIAGRAM**

## Description of Diabetic Retinopathy:

* + 1. **Image Acquisition:**

There is a dataset consists four different types of retinopathy (Hard exudates, softexudates, hemorrhages and red small dots). Among those images select anyone of the image to classify.

## Preprocessing:

In preprocessing, two plane conversions is done by converting into gray format if the taken image as supposed to be three plane image.

## INPUT IMAGE

* Initially the image is taken with the extension and resized according to the requirement.
* Preprocessing is used for reshaping and moulding the input data so that it can be fed into the CNN model.
* Noise from the image is removed or reduced to acceptable levels. Certain features are enhanced. Finally, the image is grey-scaled. **ENHANCEMENT :**

Enhance the features of the images where that taken by the source. Images are filtered into gray scaled images that image some features are extract to get a image with lesser signal to noise ratio (SNR). Extraction of intensity- t, varience-y, skewness-X, Area- I, Mean- M, Standard deviation –s

,Entropy-E, Histogram-D.

The image enhancement technique is to make the digital picture more appealing to our eyes, for example, making the images smooth or sharp. This is an important topic in digital image processing. It can help humans and computer vision algorithms obtain accurate information from the enhanced images. The visual quality and certain image properties, such as brightness, contrast, signal-to-noise ratio, resolution, edge sharpness, and color accuracy were improved through the enhancement process. Recently, many image enhancement methods have been developed based on various digital image processing techniques and applications. The enhanced image will provide useful information for post-processing, especially in segmentation stage Image enhancement is used in every field place for example, medical representation study, analysis of imagery from satellites etc.

Histogram transformation is considered one of the fundamental processes for image enhancement of gray level images, which facilitates subsequent higher level operations such as detection and identification. Histogram equalization and contrast manipulations are well- known methods for enhancing the contrast of a given image but most of them tend to be heuristic based on deep expert knowledge for image processing. Hence these techniques require a large amount of analysis and computation because of complicated formulations. Histogram equalization provides maximum information contained in the image which indirectly modifies the image histogram.

Optimization plays an imperative role in robotics, artificial intelligence, operational research, and different connected fields. It is the process of trying to find the best possible solution to an optimization problem within a reasonable time limit. Several evolutionary algorithms such as Histogram Equalization (HE), Automatic Brightness and Contrast Optimization with Optional Histogram Clipping (ABCOOHC), Automatic Gain Control (AGC), Brightness Preserving Bi-Histogram Equalization (BBHE), CLAHE and Dualistic Sub-Image Histogram Equalization (DSIHE) have been introduced in recent years in the field of image processing because of their fast computing ability.

Result images converted into GLCM Matrix that code was developed in to glcm tool

box.

Concluding that Entropy, Energy and homogeneity are features that can be selected for accurate classification.

## THRESHOLDING:

**S**egmentation of the cells are used for thresholding but can find the accurate results. Image thresholding is a type of image segmentation that divides the

foreground from the background in an image. Technique implemented has the pixel values that are assigned corresponding to the provided threshold values. In computer vision, thresholding is done in grayscale images.

In simple thresholding, all pixel values those are greater than the specific threshold value, assign to standard value. It compares pixel values with special threshold value. After separating the pixel, see the segmented images according to threshold values. Threshold techniques are mainly divided in to 3 categories based on the threshold operator.

* Global → threshold operator depends on the gray values of the pixel
* Local → threshold operator depends on the gray values of the pixel and local properties
* Dynamic → threshold operator depends on the gray values of the pixel and local properties and it’s position.

GLCM

* A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray- level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. (The texture filter functions, described in Calculate Statistical Measures of Texture cannot provide information about shape, that is, the spatial relationships of pixels in an image.)
* After you create the GLCMs using graycomatrix, you can derive several statistics from them using graycoprops. These statistics provide information about the texture of an image.

## Feature Extraction

Feature extraction is to extract the parameters of image to characterize the dermatological features of melanoma, and performing the diagnosis based on these parameters. Clinicians rely on the features of melanoma. The method of diagnosis applies for diagnosis is important to select the features. For instance, asymmetry and pigmented network are respectively the features in ABCD-rule and pattern analysis. Actually, the features evaluation of melanoma diagnosis is visually very difficult, because the content of information in dermatoscopic images is very complicated and entirely requires the experienced physicians.

The diagnosis methods to determine melanoma lesions in screening process by non- dermatologists are listed as ABCD rule, ABCD-E criteria, and Glasgow 7- point checklist. ABCD rule proposed by Friedman et al.[170] consist four criteria: Asymmetry, Border irregularity, Color variegation and Diameter 6 mm. ABCD- E is the extended type of ABCD which incorporate evolving lesion over time. Glasgow 7-point checklist consist 7 criteria: size, shape, color, inflammation, sensory change, diameter7 mm, crusting or bleeding. The diagnosis methods to determine melanoma lesions by dermoscopic images has been developed as ABCD rule, ABCD-E criteria, ABC-point list [A(A)BCDE], 7-point checklist, 7 features 3- point checklist, Pattern analysis, Menzies method.

The ABCD rule of dermoscopy consist four criteria: Asymmetry, Border sharpness, Color variegation and Differential structures. The ABCDE consist: Border irregularity, Colorvariegation, Diameter, Evolving and Other features. The7-point checklist consist seven criteria: Atypical pigment network, Blue- whitish veil, Atypical vascular pattern, Irregular

streaks, Irregular dots/globules, Irregular blotches and Regression structures. Pattern analysis consists: Global patterns and Local features. According to, Symmetry has achieved the highest weight in ABCD rule of dermatoscope. Stolz et al. indicated that, the 96% of asymmetry in melanoma cases had score 2 (both axes represent asymmetry) while it was just about 24.2% in benign images.

Many researches have considered the asymmetry according to the axis of symmetry in the tumor. The axis of symmetry may be identified using Fourier transform, best-fit ellipse,

diameter length, principal axis. Thereafter, the both created areas by the axis are differentiated. In many studies, the roundness, compactness and thinness of lesion have been considered as appropriate properties of the skin cancer images and in, have been considered as accurate geometry variables. In, the symmetry distance (SD) has been introduced as another measure in images. Seidenari et al. presented a method to estimate the distribution in skin lesions. They purpose was to determine the effectiveness of distribution parameters to identify the melanoma from the normal ones. They found out about the non- homogeneity of lesion region; they computed the mathematical parameters such as mean, variance, and Euclidean distance.

Manousaki et al. proposed to estimate the distribution irregularity using the fractal dimension in the surface of the lesion. Also, In, the standard deviation and mean are calculated in six colour spaces. In another approach, the different statistical properties of standard deviation, energy, mean and entropy are computed as extracted features. The Neural Network has been trained using these features and the accuracy of 79% was achieved. The Gray Level Co-occurrence Matrix (GLCM) as another popular method to extract the image features has been employed by different researchers in various applications Many other researches have been reported on feature extraction of skin cancer in the literature.

## Segmentation

A great challenge of research and development activities have recently highlighted in segmenting of the skin cancer images. Segmentation as an essential issue in digital image processing is used for image description and classification. The various properties in shape, brightness, colour, texture may be applied to assist the segmentation of skin lesion. However, during recent decades many algorithms have been proposed for detection of lesions in skin cancer images. Histogram thresholding which separate the area of interest (ROI) and background using one or multiple threshold values.

Region-based methods which incorporate the pixels into their similar regions using region- splitting and region-merging algorithms. Edge-based methods in which the edges of lesions are determined using the edge operators Active- contour methods in which the contours in the shape are determined to be evolved using curve evolution techniques. Morphological methods determine the seeds and employ the watershed transform for identifying the contours in an object. Colour- clustering methods employ the unsupervised clustering algorithms to generate homogeneous areas by separating the colour space. Soft-computing methods employ different soft- computing techniques to classify the pixels. Model-based methods in which the image is considered as random fields and the model is parameterized using optimization methods.

In segmentation area, clustering as a process of classifying a set of objects into classes with similar characteristics has been widely applied in many areas such as image processing, machine learning, pattern recognition, data mining, and statistics. Recently clustering algorithms found crucial applications in medical imaging field. In these algorithms, the number of clusters, initial centers of each cluster and selecting the proper parameters are the main issues. Different researchers dedicated time and effort to improve these techniques to apply in detection systems. A segmentation algorithm based on fuzzy c- means in which the histogram maxima’s are employed to determine the number of clusters.

## Histogram Equalization:

Histogram equalization is a technique for adjusting image intensities to enhance contrast. Because of this enhancement visual quality will be little bit better and easy to analysis. The values will be varied upto 256.

## Algorithm Implementation:

Algorithm is Color Histogram and Skin Locus modal used to classify the retinal images and features will be extracted.

## Classifying Result:

By using morphology technique the noises will be reduced for the classified images and we will obtain as desired one and text will be used to mention the classified type on images.

**Algorithm used:**

# CNN

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are:

* Convolutional layer
* Pooling layer
* Fully-connected (FC) layer

The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object.

**Convolutional Layer**

The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map. Let’s assume that the input will be a color image, which is made up of a matrix of pixels in 3D. This means that the input will have three dimensions—a height, width, and depth—which correspond to RGB in an image. We also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution.

The feature detector is a two-dimensional (2-D) array of weights, which represents part of the image. While they can vary in size, the filter size is typically a 3x3 matrix; this also determines the size of the receptive field. The filter is then applied to an area of the image, and a dot product is calculated between the input pixels and the filter. This dot product is then fed into an output array. Afterwards, the filter shifts by a stride, repeating the process until the kernel has swept across the entire image. The final output from the series of dot products from the input and the filter is known as a feature map, activation map, or a convolved feature.

After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model.

As we mentioned earlier, another convolution layer can follow the initial convolution layer. When this happens, the structure of the CNN can become hierarchical as the later layers can see the pixels within the receptive fields of prior layers. As an example, let’s assume that we’re trying to determine if an image contains a bicycle. You can think of the bicycle as a sum of parts. It is comprised of a frame, handlebars, wheels, pedals, et cetera. Each individual part of the bicycle makes up a lower-level pattern in the neural net, and the combination of its parts represents a higher-level pattern, creating a feature hierarchy within the CNN.

Pooling Layer

Pooling layers, also known as downsampling, conducts dimensionality reduction, reducing the number of parameters in the input. Similar to the convolutional layer, the pooling operation sweeps a filter across the entire input, but the difference is that this filter does not have any weights. Instead, the kernel applies an aggregation function to the values within the receptive field, populating the output array. There are two main types of pooling:

* **Max pooling:** As the filter moves across the input, it selects the pixel with the maximum value to send to the output array. As an aside, this approach tends to be used more often compared to average pooling.
* **Average pooling:** As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.

While a lot of information is lost in the pooling layer, it also has a number of benefits to the CNN. They help to reduce complexity, improve efficiency, and limit risk of overfitting.

Fully-Connected Layer

The name of the full-connected layer aptly describes itself. As mentioned earlier, the pixel values of the input image are not directly connected to the output layer in partially connected layers. However, in the fully-connected layer, each node in the output layer connects directly to a node in the previous layer.

This layer performs the task of classification based on the features extracted through the previous layers and their different filters. While convolutional and pooling layers tend to use ReLu functions, FC layers usually leverage a softmax activation function to classify inputs appropriately, producing a probability from 0 to 1.

Convolutional neural networks and computer vision

Convolutional neural networks power image recognition and computer vision tasks. [Computer vision](https://www.ibm.com/topics/computer-vision) is a field of artificial intelligence (AI) that enables computers and systems to derive meaningful information from digital images, videos and other visual inputs, and based on those inputs, it can take action. This ability to provide recommendations distinguishes it from image recognition tasks. Some common applications of this computer vision today can be seen in:

* **Marketing:** Social media platforms provide suggestions on who might be in photograph that has been posted on a profile, making it easier to tag friends in photo albums.
* **Healthcare:** Computer vision has been incorporated into radiology technology, enabling doctors to better identify cancerous tumors in healthy anatomy.
* **Retail:** Visual search has been incorporated into some e-commerce platforms, allowing brands to recommend items that would complement an existing wardrobe.
* **Automotive**: While the age of driverless cars hasn’t quite emerged, the underlying technology has started to make its way into automobiles, improving driver and passenger safety through features like lane line detection.

## DISEASE EXPLANATION

* + - 1. **DIABETIC RETINOPATHY**
         * Diabetic retinopathy is an eye condition that can cause vision loss and blindness in people who have diabetes. It affects blood vessels in the retina (the light-sensitive layer of tissue in the back of your eye).

Stage 1: Mild nonproliferative diabetic retinopathy. ...

Stage 2: Moderate nonproliferative diabetic retinopathy. ...

Stage 3: Severe nonproliferative diabetic retinopathy. ...

Stage 4: Proliferative diabetic retinopathy

* + - * + Diabetic retinopathy is caused when high blood sugar damages blood vessels in the retina (a light-sensitive layer of cells in the back of the eye). Damaged blood vessels can swell and leak, causing blurry vision or stopping blood flow.

## Symptoms of diabetic retinopathy

gradually worsening vision.

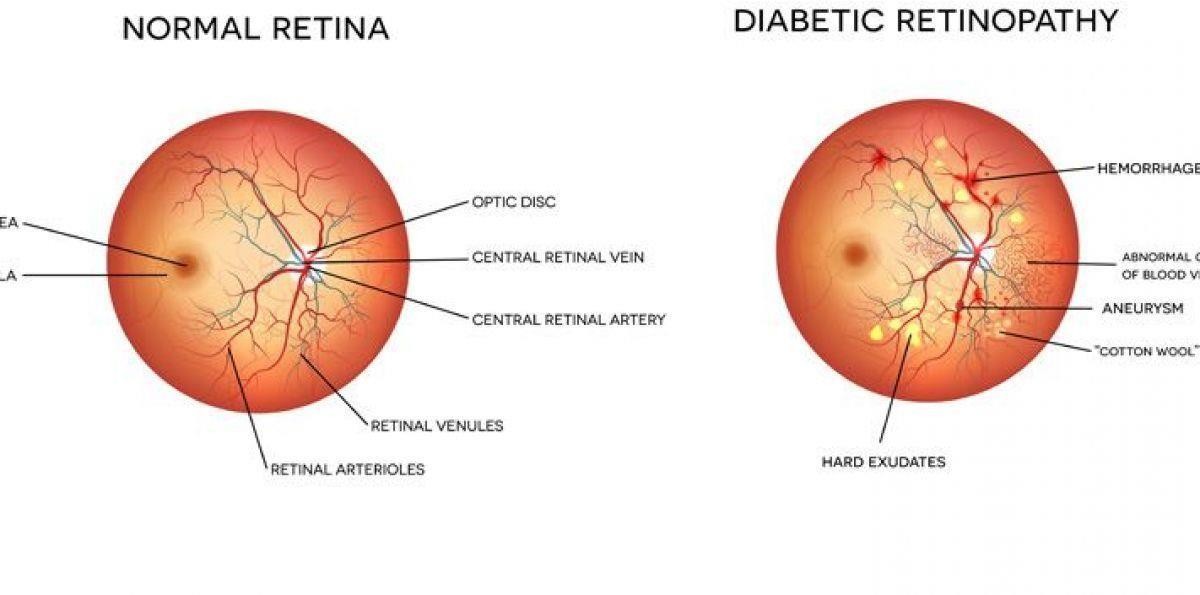
sudden vision loss.

shapes floating in your field of vision (floaters)

blurred or patchy vision.

eye pain or redness.

difficulty seeing in the dark.



**Fig 2.5.7.1 RETINOPATHY**

* + - 1. **GLAUCOMA**
         * Glaucoma is a group of eye diseases that can cause vision loss and blindness by damaging a nerve in the back of your eye called the optic nerve. The symptoms can start so slowly that you may not notice them. The only way to find out if you have glaucoma is to get a comprehensive dilated eye exam.
         * Glaucoma is a chronic, progressive eye disease caused by damage to the optic nerve, which leads to visual field loss. One of the major risk factors is eye pressure. An abnormality in the eye's drainage system can cause fluid to build up, leading to excessive pressure that causes damage to the optic nerve.

## Risk factors

High internal eye pressure, also known as intraocular pressure.

Age over 55.

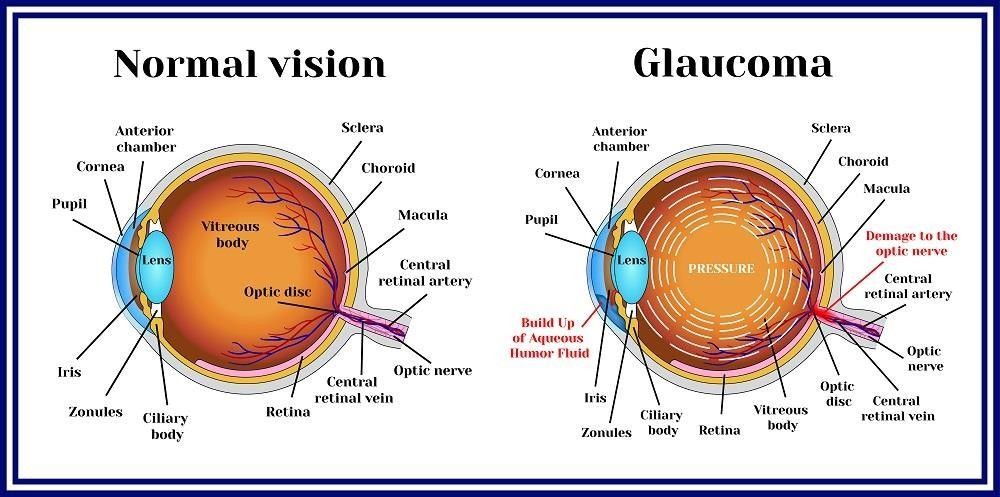
Black, Asian or Hispanic heritage.

Family history of glaucoma.

Certain medical conditions, such as diabetes, migraines, high blood pressure and sickle cell anemia.

Corneas that are thin in the center.

* + - * + Early stage -> Hazy or blurred vision: Distorted or blurry vision accompanied by other symptoms. Eye pain: Severe pain around your eyes & head. Eye redness: Red eyes caused by increased eye pressure. Colored halos around lights: Colored bright circles forming around light sources.



**Fig 2.5.7.2**

**GLAUCOMA**

* + - 1. **CATARACT**
         * A cataract is a cloudy area in the lens of your eye (the clear part of the eye that helps to focus light). Cataracts are very common as you get older. In fact, more than half of all Americans age 80 or older either have cataracts or have had surgery to get rid of cataracts.
         * Common Types of Cataracts. Age related is by far the most common type of cataract and it is divided into 3 types based on the anatomy of the human lens. There are Nuclear Sclerotic, Cortical and Posterior Subcapsular Cataracts.

## Signs and symptoms of cataracts include:

Clouded, blurred or dim vision

Increasing difficulty with vision at night

Sensitivity to light and glare

Need for brighter light for reading and other activities

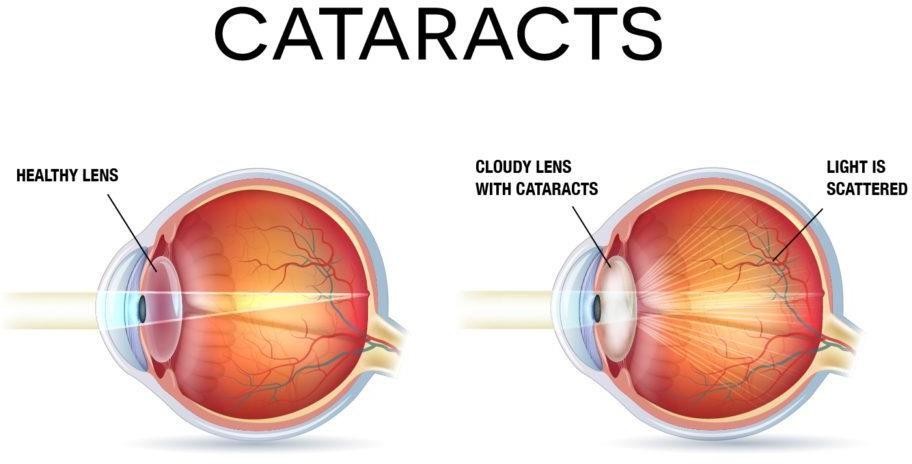
Seeing "halos" around lights

Frequent changes in eyeglass or contact lens prescription

Fading or yellowing of colors

Double vision in a single eye

* + - * + Most cataracts develop when aging or injury changes the tissue that makes up the eye's lens. Proteins and fibers in the lens begin to break down, causing vision to become hazy or cloudy.



**Fig 2.5.7.3 CATARACT**

## CHAPTER 6

**SYSTEM REQUIREMENTS SPECIFICATION**

## SOFTWARE REQUIREMENT

* + 1. Tool : Matlab 2014a
    2. Toolbox : Image Processing

## HARDWARE REQUIREMENT

* + 1. SYSTEM : Pentium IV 2.4 GHz
    2. HARD DISK : 40 GB
    3. RAM : 2 GB

## CHAPTER 7

## SYSTEM IMPLEMENTATION

**7.1 .1 SOFTWARE OVERVIEW**

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java You can use MATLAB for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

## Key Features

High-level language for numerical computation, visualization, and application development

Interactive environment for iterative exploration, design, and problem solving

Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations

Built-in graphics for visualizing data and tools for creating custom plots Development tools for improving code quality and maintain ability and maximizing Performance

Tools for building applications with custom graphical interfaces.

Functions for integrating MATLAB based algorithms with external applications and Languages such as C, Java, .NET, and Microsoft Excel

## Numeric Computation

MATLAB provides a range of numerical computation methods for analyzing data, developing algorithms, and creating models. The MATLAB language includes mathematical functions that support common engineering and science operations Core math functions use processor-optimized libraries to provide fast execution of vector and matrix calculations.

Available methods include:

* + - * + Interpolation and regression
        + Differentiation and integration
        + Linear systems of equations
        + Fourier analysis
        + Eigen values and singular values
        + Ordinary differential equations (ODEs)
        + Sparse matrices

MATLAB add-on products provide functions in specialized areas such as statistics, optimization, signal analysis, and machine learning.

## Data Analysis and Visualization

MATLAB provides tools to acquire, analyze, and visualize data, enabling you togain insight into your data in a fraction of the time it would take using spreadsheets or traditional programming languages. You can also document and share your results through plots and reports or as published MATLAB code.

## Acquiring Data

MATLAB lets you access data from files, other applications, databases, and external devices. You can read data from popular file formats such as Microsoft Excel; text or binary files; image, sound, and video files; and scientific files such as net CDF and HDF. File I/O functions let you work with data files in any format. Using MATLAB with add-on products, you can acquire data from hardware devices, such as your computer’s serial port or sound card, as well as stream live, measured data directly into MATLAB for analysis and visualization. You can also communicate with instruments such as oscilloscopes, function generators, and signal analyzers.

## Analyzing Data

MATLAB lets you manage, filter, and pre-process your data. You can perform exploratory data analysis to uncover trends, test assumptions, and build descriptive models. MATLAB provides functions for filtering and smoothing, interpolation, convolution, and fast Fourier transforms (FFTs). Add-on products provide capabilities for curve and surface fitting, multivariate statistics, spectral analysis, image analysis, system identification, and other analysis tasks.

## Visualizing Data

MATLAB provides built-in 2-D and 3-D plotting functions, as well as volume visualization functions. You can use these functions to visualize and understand data and communicate results. Plots can be customized either interactively or programmatically. The MATLAB plot gallery provides examples of many ways to display data graphically in MATLAB. For each example, you can view and download source code to use in your MATLAB application.

## Documenting and Sharing Results

You can share results as plots or complete reports. MATLAB plots can be customized to meet publication specifications and saved to common graphical and data file formats. You can automatically generate a report when you execute a MATLAB program. The report contains your code, comments, and program results, including plots. Reports can be published in a variety of formats, such as HTML, PDF, Word, or Latex.

## Programming and Algorithm Development

MATLAB provides a high-level language and development tools that let you quickly develop and analyze algorithms and applications.

## The MATLAB Language

The MATLAB language provides native support for the vector and matrix operations that are fundamental to solving engineering and scientific problems, enabling fast development and execution. With the MATLAB language, you can write programs and develop algorithms faster than with traditional languages because you do not need to perform low-level administrative tasks such as declaring variables, specifying data types, and allocating memory. In many cases, the support for vector and matrix operations eliminates the need for for-loops. As a result, one line of MATLAB code can often replace several lines of C or C++ code. MATLAB provides features of traditional programming languages, including f low control, error handling, and object-oriented programming (OOP). You can use fundamental data types or advanced data structures, or you can define custom data types. You can produce immediate results by interactively executing commands one at a time. This approach lets you quickly explore multiple options and iterate to an optimal solution. You can capture interactive steps as scripts and functions to reuse and automate your work. MATLAB add- on products provide built-in algorithms for signal processing and communications, image and video processing, control systems, and many other domains. By combining these algorithms with your own, you can build complex programs and applications.

## Development Tools

MATLAB includes a variety of tools for efficient algorithm development, including:

**Command Window** –Lets you interactively enter data, execute commands and programs, and display results

**MATLAB Editor**–Provides editing and debugging features, such as setting break points and stepping through individual lines of code

**Code Analyzer**–Automatically checks code for problems and recommends modifications to maximize performance and maintainability

**MATLAB Profiler**–Measures performance of MATLAB programs and identifies areas of code to modify for improvement

Additional tools compare code and data files, and provide reports showing file dependencies, annotated reminders, and code coverage.

## Integration with other languages and applications

You can integrate MATLAB applications with those written in other languages.

From MATLAB, you can directly call code written in C, C++, Java, and .NET. Using the MATLAB engine library, you can call MATLAB code from C, C++, or FORTRAN applications.

## Performance

MATLAB uses processor-optimized libraries for fast execution of matrix and vector computations. For general-purpose scalar computations, MATLAB uses its just-in-time (JIT) compilation technology to provide execution speeds that rival those of traditional programming languages. To take advantage of multi core and multiprocessor computers, MATLAB provides many multithreaded linear algebra and numerical functions. These functions automatically execute on multiple computational threads in a single MATLAB session, enabling them to execute faster on multi core computers you can take further advantage of multi core desktop and other high-performance computing resources such as GPUs and clusters with add-on parallel computing products. These products provide high- level constructs that let you parallelize applications with only minor changes to MATLAB code.

## Image Acquisition

Image Acquisition Toolbox™ enables you to acquire images and video from cameras and frame grabbers directly into MATLAB and SIMULINK. You can detect hardware automatically and configure hardware properties. Advanced workflows let you trigger acquisition while processing in-the-loop, perform background acquisition, and synchronize sampling across several multimodal devices. With support for multiple hardware vendors and industry standards, you can use imaging devices ranging from inexpensive Web cameras to high-end scientific and industrial devices that meet low-light, high-speed, and other challenging requirements.

## Key features

* + 1. Support for industry standards, including DCAM, Camera Link, and GigE Vision
    2. Support for common OS interfaces for webcams, including Direct Show, QuickTime, and video4linux2
    3. Support for a range of industrial and scientific hardware vendors
    4. Multiple acquisition modes and buffer management options
    5. Synchronization of multimodal acquisition devices with hardware triggering
    6. Image Acquisition app for rapid hardware configuration, image acquisition, and live video previewing
    7. Support for C code generation in Simulink

## COLOUR HISTOGRAM

In image processing and [photography](https://en.wikipedia.org/wiki/Photography), a color histogram is a representation of the distribution of colours in an [image](https://en.wikipedia.org/wiki/Image). For digital images, a color histogram represents the number of [pixels](https://en.wikipedia.org/wiki/Pixel) that have colours in each of a fixed list of color ranges, that span the image's [color space](https://en.wikipedia.org/wiki/Color_space), the set of all possiblecolours.

The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like [RGB](https://en.wikipedia.org/wiki/RGB_color_space) or [HSV](https://en.wikipedia.org/wiki/HSV_color_space). For [monochromatic images](https://en.wikipedia.org/wiki/Monochromatic_image), the term intensity histogram may be used instead. For multi-spectral images, where each pixel is represented by an arbitrary numberof measurements (for example, beyond the three measurements in RGB), the color histogram is *N*-dimensional, with N being the number of measurements taken. Each measurement has its own wavelength range of the light spectrum, some of which may be outside the visible spectrum.

## SKIN LOCUS MODEL

Although different people have different skin color, but several studies have shown that the major difference lies largely in their intensity rather than their chrominance. Several value distribution models have been compared in different color spaces (RGB, HSV, YCbCr, etc.) These distribution models have shown some efficiency in extracting skin-like regions under certain limited conditions.

When only the chromaticity information is considered, also a relative robustness against intensity changes is achieved. However, this will not solve all the problems related to illumination and camera calibrations: skin chromaticities depend on the prevailing illumination and camera calibration light source. The more these two lighting factors differ, the bigger shift in chromaticities. Moreover, illumination color can be non-uniform over the face (in this case, even a proper calibration is not enough). To solve these problems, we propose to use the skin locus which has performed well with images under widely varying conditions. Skin locus (after Storing ) is the range of skin chromaticities under varying illumination/camera calibration conditions in NCC (normalized color coordinate) space. In NCC space, intensity is defined as I=R+G+B and chromaticities are r=R/I, g=G/I and b=B/l. Because r+g+b=l, only the intensity and two chromaticity coordinates are enough for specifying any color uniquely. We considered r-b coordinates to obtain both robustness against intensity variance and good overlap of chromaticities of different skin colours. The lower bound is defined by a five-degree polynomial function. Pixels with chromaticity (r, b) are labelled as skin or not using the constraint.

**RESULT AND OUTPUT**

* + - * This system used to find out the eye diseases like retinopathy, glaucoma, cataract. We use eye image sets, the Image will undergo a standard method of applying image processing which include image acquisition, pre- processing, and CNN algorithm used to feature extraction followed by exact identification of disease.



**Fig 1 diabetic retinopathy disease detected eye**



**Fig 2 glaucoma disease detected eye**



**Fig 3 cataracts disease detected eye**

**CODE:**

clc;

clear all; close all;

while(1)

ch = menu('RETINOPATHY SEGMENTATION','Input

Image','Preprocessing','Feature Extraction','CATARACT

Localization','Morphological Operation','Cluster',' SVM Segmentation','Exit');

if(ch==1)

[I,path]=uigetfile('\*.jpg','select a input image'); str=strcat(path,I);

s=imread(str); figure,imshow(s),title('Input image'); [m1 m2 m3]=size(s);

end

end

if size(s,3)==3 g=rgb2gray(s);

if(ch==2)

num\_iter = 10; delta\_t = 1/7; kappa = 15;

option = 1; ede=im2bw(s); imie=edge(ede,'canny');

disp('Preprocessing image please wait . . .'); ad = process(s,num\_iter,delta\_t,kappa,option); adj = uint8(ad);

figure,

subplot 121, imshow(s,[]),title('Input image'); subplot 122, imshow(adj,[]),title('Fitered image');

end if(ch==3)

if size(s,3)==3 s=rgb2gray(s);

end

GLCMS = graycomatrix(s,'Offset',[2 0;0 2]); stats1 =

graycoprops(GLCMS,{'contrast','homogeneity','Energy','Correlation'})

;

x1 = stats1.Correlation(1); disp(x1);

x2 = stats1.Correlation(2); disp(x2);

x3 = stats1.Energy(1); disp(x3);

x4 = stats1.Energy(2); disp(x4);

x5 = stats1.Contrast(1); disp(x5);

x6 = stats1 .Contrast(2); disp(x6);

x7=stats1.Homogeneity(1); disp(x7); x8=stats1.Homogeneity(2); disp(x8);

end

if ch(ch==4)

features = extractHOGFeatures(s); figure,imshow(features);

end if(ch==5)

cex=im2bw(s,0.8); hlex=strel('disk',1,0); cex=imclose(cex,hlex); c1loc=bwareaopen(cex,250); c2les=bwboundaries(c1loc);

figure,imshow(s),title('GLAUCOMA Boundary') hold on

## CHAPTER 8 CONCLUSION

We developed and prospectively validated an automatic image algorithm for HEs detection. The algorithm detects HE lesions based on colour, using a statistical classification; and by the sharpness of its edges, applying a Kirsch operator. Our results demonstrate that the system is well suited to complement the screening of DR and may be use to help the ophthalmologists in their daily practice.

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