

ANALYSIS OF RETINAL IMAGES FOR IDENTIFICATION OF DIABETES USING CNN AND DEEP NEURAL NETWORK

Submitted in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering

by

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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A++" by NAAC

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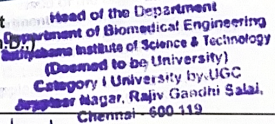
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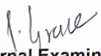
This is to certify that this Project Report is the bonafide work of RUFINA MAGDALIN SHALLOWM S(40240028), ISHA R INGROLE (4040045) who have done the project work as a team and carried out the project entitled "**ANALYSIS OF RETINAL IMAGES FOR IDENTIFICATION OF DIABETES USING CNN AND DEEP NEURAL NETWORK**" under our supervision from November 2023 to April 2024.


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DECLARATION

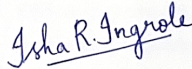
We, RUFINA MAGDALIN SHALLOWM S (40240028) and ISHA R INGROLE (40240045), hereby declare that the Project Report entitled *"ANALYSIS OF RETINAL IMAGES FOR IDENTIFICATION OF DIABETES USING CNN AND DEEP NEURAL NETWORK"* done by us under the guidance of Dr. J PREMKUMAR (Internal) at Sathyabama Institute of Science and Technology is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

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ABSTRACT

In-depth exploration of Fundus Image Analysis techniques, specifically tailored for the detection of Glaucoma and Diabetic Retinopathy (DR). It focuses on existing systems that utilize cutting-edge technologies such as Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN), highlighting their limitations. In response, the project proposes an innovative integration of CNN and DNN algorithms to enhance accuracy in identifying different stages of these ocular diseases, crucial for effective treatment strategies. By harnessing the robust capabilities of CNN and DNN, alongside the application of gradient boosting techniques for refined feature extraction and classification, the proposed system aims to provide superior performance in clinical settings. Through rigorous experimentation, the project showcases the potential of these algorithms, particularly emphasizing their efficiency in aiding medical professionals with early detection and staging of Glaucoma and DR. In today's health landscape, where various ailments impede daily activities, eye diseases like Glaucoma and DR stand out as significant contributors to vision loss. The progressive nature of these conditions, characterized by damage to the optic nerve in Glaucoma and changes in retinal blood vessels in DR, underlines the urgent need for early detection. The project methodology follows a standard image processing pipeline, from acquisition to pre-processing, feature extraction, and ultimately precise disease identification using a feed-forward neural network classifier. This proposed system's anticipated enhancement in efficiency and accuracy compared to existing methods represents a significant advancement in medical image analysis for ocular diseases. Its potential impact on patient care and management offers a robust solution for early disease detection and staging, promising to improve outcomes in the realm of ocular health.

Keywords: Fundus Image Analysis, Glaucoma Detection, Diabetic Retinopathy (DR). Deep Neural Networks (DNN), Convolutional Neural Networks (CNN).

CONTENTS

CHAPTER No.	CHAPTERS	PAGE No.
	ABSTRACT	V
	LIST OF CONTENTS	VI
	LIST OF FIGURES	VIII
	LIST OF ABBREVIATIONS	IX
1	INTRODUCTION	1
2	LITERATURE SURVEY	2
	2.1 SURVEY	2
3	AIM AND SCOPE	12
4	MATERIALS AND METHODS	13
	4.1 METHODOLOGY	13
	4.1.1 Deep Learning	13
	4.1.2 Mat-lab	15
	4.1.2.1 Interactive Environment	15
	4.1.2.2 Matrix and Array Operations	15
	4.1.2.3 Rich Library of Functions	15
	4.1.2.4 Data Analysis and Visualization	15
	4.2 MODULES AND METHODS	16
	4.2.1 Data Collection	16
	4.2.2 Pre processing	16
	4.2.3 Data Splitting	16
	4.2.4 Feature Extraction	16
	4.2.5 Model Selection	16
	4.2.6 Model Training	16
	4.2.7 Hyper parameter Tuning	16
	4.2.8 Module Evaluation	17
	4.2.9 Post-processing	17
	4.3 PROPOSED METHOD	17
	4.3.1 Data Collection	18
	4.3.2 Pre-Processing	18
	4.3.3 Feature Extraction	19
	4.3.4 Classification	19

	4.4 ALGORITHMS	20
	4.4.1 Feed Forward Neural Networks	20
	4.4.2 Convolution Neural Networks	21
	4.4.3 Deep Neural Networks	22
	4.5 SOFTWARE AND HARDWARE USED	23
5	RESULTS AND DISCUSSION	25
	5.1 RESULT	25
	5.1.1 Feed Forward Neural Network	25
	5.1.2 Convolutional Neural Network	28
	5.1.3 Deep Neural Network	31
	5.2 DISCUSSION	34
6	SUMMARY AND CONCLUSIONS	35
	6.1 SUMMARY	35
	6.2 CONCLUSIONS	36
	REFERENCES	37

LIST OF FIGURES

FIGURE No.	CONTENT	PAGE No.
4.1	Architecture Diagram of Feed Forward Neural Network	18
4.2	An example of Feed Forward Neural Network	21
4.3	Convolutional Neural Network	22
4.4	Deep Neural Network	23
5.1	Feed Forward Neural Network: Glaucoma Detected	25
5.2	Feed Forward Neural Network: Diabetic Detected	26
5.3	Feed Forward Neural Network: Confusion Matrix	27
5.4	Convolutional Neural Network: Glaucoma Detected	28
5.5	Convolutional Neural Network: Diabetic Detected	29
5.6	Convolutional Neural Network: Confusion Matrix	30
5.7	Deep Neural Network: Glaucoma Detected	31
5.8	Deep Neural Network: Diabetic Detected	32
5.9	Deep Neural Network: Confusion Matrix	33

LIST OF ABBREVIATION

ABBREVIATION	EXPANSION
DR	Diabetic Retinopathy
FNN	Feed Forward Neural Network
CNN	Convolutional Neural Network
DNN	Deep Neural Network
GLCM	Gray Level Co-Occurrence Matrix
GAN	Generative Adversarial Network (GAN)
AUC-ROC	The Area Under the Receiver Operating Characteristic curve
CGANs	Conditional Generative Adversarial Networks
CLAHE	Contrast Limited Adaptive Histogram Equalization
MLPs	Multilayer perceptrons

CHAPTER 1

INTRODUCTION

Eye diseases, notably Diabetic Retinopathy (DR) and Glaucoma, stand as critical areas of medical research due to their potential for irreversible vision loss. DR, a complication of diabetes, poses a significant threat by damaging the retina's delicate blood vessels. The resulting abnormalities, such as blood and lipoprotein fluid leakage, underscore the urgency of early detection. Glaucoma, characterized by increased intraocular pressure, gradually damages the optic nerve, leading to vision loss or blindness if left untreated. Timely identification of these conditions is crucial, emphasizing the importance of routine eye exams. Early symptoms serve as vital indicators for effective intervention, allowing for prompt treatment before irreversible damage occurs. Regular eye exams are the cornerstone of early detection, providing the best opportunity for preserving vision. Non-invasive techniques like retinal fundus imaging play a pivotal role in this context, particularly in diagnosing Glaucoma by measuring the retinal nerve fiber layer's thickness. These imaging methods offer accessibility and utility, proving invaluable in healthcare settings, especially during screening initiatives. Their significance is magnified in underserved communities, where access to specialized eye care is limited. By enabling prompt identification and management of sight-threatening conditions, these techniques ensure that individuals receive timely intervention, safeguarding their vision and overall quality of life. This report delves into the significance of these non-invasive imaging methods and their role in the early detection and management of DR and Glaucoma, particularly in populations with limited access to specialized care. This study was conducted by Duff J, *et al.*, (2015).

CHAPTER 2

LITERATURE SURVEY

2.1 SURVEY

Modeling and Enhancing Low-Quality Retinal Fundus Images introduced a novel approach known as the Clinically Oriented Fundus Enhancement Network (COFE-Net). The primary objective of COFE-Net is to address the challenges associated with low-quality retinal fundus images. These images are often hindered by issues like poor lighting, motion blur, and camera artifacts. COFE-Net is specifically designed to target global degradation factors affecting the entire image, such as uneven illumination and noise. This deep learning-based neural network enhances the quality of these images in a clinically relevant manner, making them more informative and useful for medical professionals. Ultimately, COFE-Net aims to improve the accuracy of diagnosis and treatment in the field of ophthalmology by providing enhanced and diagnostically valuable retinal fundus images (Ziyi Shen *et al.*, 2021).

Introduced algorithm aimed at enhancing the quality of retinal images to bolster the diagnostic capabilities for Diabetic Retinopathy (DR). Diabetic Retinopathy is a critical eye condition associated with diabetes, and accurate diagnosis is highly dependent on the quality of retinal images. (Saif Hameed Abbood *et al.*, 2022) The algorithm leverages deep learning techniques to enhance these images effectively. By improving image quality, it enables a higher standard in the diagnosis of DR. Enhancements likely involve reducing noise, correcting issues related to illumination, and emphasizing crucial details. Ultimately, this research contributes to the advancement of diagnostic capabilities, ensuring that medical professionals can more accurately identify and manage Diabetic Retinopathy, which is vital for preventing vision loss in diabetic patients.

"A Hybrid Global-Local Representation CNN Model for Automatic Cataract Grading" presents an innovative approach for cataract grading using Convolutional Neural Networks (CNNs). CNNs are employed to directly learn features from the input data, which in this context are likely cataract-affected images. The novelty lies in the utilization of a deep neural method to explore how the CNN characterizes cataract conditions layer by layer. This hybrid model combines both global and local representation techniques to enhance the accuracy of cataract grading. The CNN is used to extract features from the entire image, providing a global perspective on cataract severity. Simultaneously, the deep neural method dissects these features layer by layer, offering a more detailed and local view of the cataract condition within the eye. This dual approach likely results in a more comprehensive and precise grading system for cataracts, which is valuable for effective diagnosis and treatment planning in ophthalmology (Linglin Zhang *et al.*, 2020).

"Eye Disease Detection Using Machine Learning" introduces a system designed to streamline the detection of various eye diseases, including cataract, glaucoma, and retinal diseases in patients. This system harnesses the power of machine learning algorithms to enable efficient and accurate diagnosis. The primary objective of this system is to provide a user-friendly and accessible platform for both medical professionals and patients to identify and assess these eye conditions. Machine learning techniques are employed to analyze and interpret various data sources, such as retinal images or patient records, to make these detections. By automating the diagnostic process, this system has the potential to significantly reduce the time and effort required for medical practitioners to reach an accurate diagnosis. Moreover, it can enhance the early detection of these eye diseases, which is critical for timely treatment and preserving patients' vision. This research represents a promising step forward in the field of ophthalmology and healthcare technology (Ahmed Al Marouf *et al.*, 2019)

"Cataract Net: An Automated Cataract Detection System Using Deep Learning for Fundus Images" presents an automated system for cataract detection using deep learning techniques. The proposed system utilizes the Adam optimizer for model optimization, a widely used method in deep learning to enhance training efficiency. To develop and train the model effectively, a substantial dataset of 1130 fundus images, consisting of both cataract and non-cataract cases, was collected. These images were augmented, increasing the dataset size to 4746 images. Data augmentation is a process where new training examples are generated from the original dataset by applying various transformations, such as rotation, scaling, or cropping. Augmentation helps improve the model's ability to generalize and detect cataracts accurately. The combination of deep learning, data augmentation, and a sizable dataset allows the Cataract Net system to provide an automated and robust solution for cataract detection in fundus images, offering potential benefits in early diagnosis and treatment of cataract-related eye conditions (Masum Shah Junayed *et al.*, 2021).

"Individualized Statistical Modeling of Lesions in Fundus Images for Anomaly Detection" focuses on improving anomaly detection in fundus images, especially for identifying lesions or abnormalities. Presently, many existing methods for anomaly detection rely on a process that involves reconstructing or segmenting the fundus image background by referencing a set of normal fundus images as a guide. This approach is based on the idea that by contrasting an input fundus image with a dataset of "normal" fundus images, any deviations or anomalies can be detected. It typically involves modeling the typical features of healthy fundus images and then identifying deviations from this norm. This method has limitations in that it may not adequately address the intricacies of individual patients' conditions and specific anomalies that don't conform to general norms. Instead of relying solely on a universal reference dataset, it seeks to develop models that better account for the unique characteristics of individual patients, enhancing the accuracy of anomaly detection in fundus images. This approach represents a promising advancement in the field of medical image analysis, improving the ability to detect various eye conditions and anomalies (Yuchen Du *et al.*, 2023).

"R Former: Transformer-Based Generative Adversarial Network for Real Fundus Image Restoration on a New Clinical Benchmark" addresses the critical role of fundus images in ophthalmology, where these images are commonly used for screening and diagnosing various eye diseases. However, a significant challenge arises from the substantial variability in the quality of fundus images due to different equipment and the expertise of the ophthalmologists capturing them. This research introduces a novel approach, R Former, which is a Generative Adversarial Network (GAN) based on the Transformer architecture. The primary objective is to restore and enhance the quality of real fundus images, irrespective of variations in acquisition methods or expertise. By leveraging the capabilities of the Transformer model and GAN, R Former aims to provide a robust solution for improving the clarity and diagnostic value of fundus images. Ultimately, this research contributes to the development of a valuable tool for ophthalmologists, assisting them in achieving more accurate and consistent diagnoses by mitigating the impact of image quality variations in fundus images. This advancement has the potential to enhance the overall effectiveness of eye disease screening and diagnosis in clinical practice (Zhuo Deng, *et al.*, 2022).

"Bridging Synthetic and Real Images: A Transferable and Multiple Consistency Aided Fundus Image Enhancement Framework" addresses a crucial challenge in the field of fundus image enhancement. The study focuses on the transition between synthetic and real fundus images, emphasizing that this domain shift poses a significant obstacle to the effective application of image enhancement models in clinical settings. While synthetic images can be useful for training and experimentation, they often differ substantially from real clinical data. This disconnect creates a generalization problem for models developed using synthetic data, as their performance may not translate well to real-world applications. The paper explores a framework designed to mitigate this issue by promoting consistency between synthetic and real 5 images. By developing transferable and multiple consistency aids, this framework aims to enhance the adaptability of image enhancement models to clinical data, making them more effective in practical scenarios (Erjian Guo *et al.*, 2023).

"Semi-Supervised Dual Stream Segmentation Network for Fundus Lesion Segmentation" highlights the significance of precise segmentation of retinal images in aiding ophthalmologists in assessing the severity of retinopathy and diagnosing systemic diseases. This segmentation is a fundamental step in identifying and analyzing fundus lesions within the retina. The complexity of the retina's structure presents a notable challenge, where various anatomical structures can significantly impact the accuracy of lesion segmentation. This complexity includes blood vessels, optic nerve, and macula, among others. The intricate interplay between these structures can make it difficult to isolate and identify pathological lesions accurately. To address this issue, the research introduces a semi-supervised dual stream segmentation network, a sophisticated approach designed to improve the accuracy of lesion segmentation in fundus images. By leveraging both labeled and unlabeled data, this framework offers a more comprehensive understanding of the diverse retinal structures, ultimately facilitating more precise and clinically relevant lesion segmentation. This research contributes to enhancing the diagnostic capabilities of ophthalmologists in assessing retinopathy and related systemic disease (Dehui Xiang *et al.*, 2023).

"Attention-Aided Generative Learning for MultiScale Multi-Modal Fundus Image Translation," aimed at addressing critical challenges in the translation of fundus images across different scales and modalities. This framework comprises three key stages: cropping, enhancement, and translation. The initial stage focuses on cropping and employs an innovative strategy centered around the optic disc. This strategy is instrumental in mitigating the scale differences between the source and 6 target image domains. By aligning the images based on the optic disc, which is a prominent and identifiable anatomical feature, the framework helps ensure a consistent scale reference for the subsequent translation process. This method offers a promising solution to the complex task of translating fundus images across varying scales and modalities, ultimately improving the accuracy and effectiveness of image processing and analysis in the field of ophthalmology. It showcases the potential of leveraging attention and generative learning to enhance multi-modal fundus image translation (Van-Nguyen Pham *et al.*, 2023).

In the realm of retinal image analysis, Gulshan and colleagues have shown impressive achievements in image classification, underscoring the potential of deep learning in this domain. They leveraged transfer learning techniques, utilizing pre-trained models, which has notably enhanced the performance of retinal image analysis. The success of deep neural networks (DNNs) in this context is attributed to their deep architectural design, allowing for effective feature extraction from complex retinal images. Transfer learning with pre-trained models enables the utilization of knowledge acquired from one task or dataset (often large and diverse) to enhance the performance on a related task, which is particularly advantageous in medical image analysis. DNNs, with their deep layers, excel at learning hierarchical representations, making them effective at capturing intricate features within retinal images, which can be vital in tasks like disease classification or anomaly detection. This progress in leveraging deep learning methodologies demonstrates significant potential for improving the accuracy and efficiency of retinal image analysis in medical diagnostics (Gulshan *et al.*, 2016).

Ting have harnessed the power of Deep Neural Networks (DNNs) for precise identification of retinal lesions. They've showcased the effectiveness of DNNs in the field of ophthalmology. Several well-established DNN architectures, such as Res Net and VGG, have been adapted for retinal lesion detection, significantly improving the accuracy of the task. In addition to DNNs, Feed forward Neural Networks (FNNs) have also been applied, although less commonly, in the context of diabetic retinopathy detection. The relative simplicity of FNN architectures makes them well-suited for certain real-time applications, where computational efficiency is paramount. While DNNs offer remarkable accuracy through their deep hierarchical layers, FNNs can be a valuable choice when the focus is on real-time or more computationally efficient solutions. The research demonstrates the versatility of neural networks in addressing different aspects of retinal image analysis, from precise lesion identification to real-time diagnostic applications in the field of ophthalmology (Ting *et al.*, 2017).

Rajalakshmi have illustrated the effectiveness of Feedforward Neural Networks (FNNs) in the context of diabetic retinopathy detection. They have demonstrated that FNNs can be valuable tools for accurate diagnosis in this domain. Typically, the Kaggle Diabetic Retinopathy Detection dataset serves as a common benchmark for evaluating the performance of these models. In their research, preprocessing steps like image resizing and contrast adjustment have been identified as crucial for preparing the retinal images as model inputs. These steps help ensure that the data is in a suitable format for effective analysis. The evaluation of these models often relies on several key metrics, including accuracy, sensitivity, specificity, and the Area Under the Receiver Operating Characteristic curve (AUC-ROC). High sensitivity is particularly emphasized because missing positive cases of diabetic retinopathy can have significant clinical consequences. In summary, the research highlights the importance of FNNs in diabetic retinopathy detection and underscores the significance of rigorous preprocessing and appropriate evaluation metrics for accurate and reliable diagnosis (Rajalakshmi *et al.*, 2015).

The authors delve into the critical field of ophthalmic imaging, which plays a pivotal role in the diagnosis and management of various eye diseases. The article covers a wide array of topics related to retinal imaging, from the technical aspects of imaging modalities to the intricate details of image analysis. It emphasizes the significance of retinal imaging in understanding retinal pathologies, offering insights into disease progression and providing essential data for clinicians. Furthermore, the article likely discusses the evolution of retinal imaging technology and its integration with advanced image analysis algorithms. This convergence has enabled the development of automated tools for the early detection and monitoring of retinal diseases. Overall, the paper serves as a valuable resource for researchers, engineers, and clinicians in the field of ophthalmic imaging and underscores its importance in modern healthcare (Michael D. Abràmoff *et al.*, 2011).

I-secret: Importance-guided Fundus Image Enhancement via Semi-Supervised Contrastive Constraining, P. Cheng present an innovative approach to enhance the quality of fundus images. This proposed method, I-secret, incorporates importance guidance and semi-supervised contrastive constraining to improve the clarity and diagnostic value of fundus images. The core concept of I-secret revolves around the notion of importance guidance, which helps prioritize the enhancement of critical regions within the image, such as pathological lesions or anatomical structures. This approach enables the algorithm to focus on the most diagnostically relevant areas. Additionally, the use of semi-supervised contrastive constraining harnesses the power of deep learning techniques to refine the image enhancement process. By integrating supervised and unsupervised learning principles, the model can effectively learn from both labeled and unlabeled data, which is particularly advantageous in the medical imaging domain. Overall, this research 9 showcases a sophisticated framework for fundus image enhancement, addressing the importance of optimizing image quality and clinical relevance while leveraging state-of the-art machine learning methods. (Cheng *et al.*, 2014).

Introduced an innovative method for enhancing the quality of eye fundus images using Conditional Generative Adversarial Networks (CGANs). This research addresses the critical need for improved image quality in ophthalmology, particularly in fundus imaging. The proposed method leverages CGANs, which are a subset of generative adversarial networks, to perform image enhancement. CGANs take into account conditional information, which is valuable for maintaining the anatomical and pathological details specific to the eye. The paper likely discusses the 11 implementation and evaluation of this method, emphasizing its ability to enhance image quality by preserving critical retinal structures while reducing noise and artifacts. This technique is instrumental in improving the accuracy of diagnostics and treatment planning for various eye conditions. In summary, this research contributes to the advancement of image enhancement techniques tailored to ophthalmic applications (A. D. P´erez *et al.*, 2020).

Transformers in Medical Imaging provides an extensive survey of the application of Transformer models in the field of medical imaging. The author explore the growing role of Transformer architectures, originally designed for natural language processing, in revolutionizing medical image analysis. They cover various aspects, including the adaptability of Transformers for different modalities such as X-rays, MRIs, and CT scans. The paper discusses how Transformers are used for tasks like disease diagnosis, image segmentation, and anomaly detection, highlighting their remarkable success and performance improvements. Furthermore, the survey addresses the challenges and future prospects of integrating Transformers in medical imaging, emphasizing the potential for increased accuracy, efficiency, and the development of specialized architectures tailored to healthcare applications. This paper serves as a valuable resource for researchers and practitioners seeking to understand the evolving landscape of medical image analysis with Transformer models (Shamshad *et al.*, 2022).

The research primarily focuses on preserving critical structural details within retinal images. The paper presents a specialized structure-preserving guided filtering technique tailored to retinal images. This technique improves image quality by reducing noise, enhancing relevant features, and preserving the structural integrity of anatomical elements. The method is particularly valuable for the analysis of the optic disc, a significant anatomical feature used in the diagnosis and evaluation of various eye conditions. This work contributes to the development of advanced image processing methods specifically designed for retinal images. By ensuring that structural information is retained during filtering, it aids in accurate and reliable optic disc analysis, ultimately benefiting the field of ophthalmology and medical image analysis (Cheng *et al.*, 2018).

Paper presented at the International Conference on ICT for Smart Society, A. W. Setiawan discuss the application of a method called CLAHE (Contrast Limited Adaptive Histogram Equalization) for the enhancement of color retinal images. The primary objective of this research is to improve the visual quality and diagnostic utility of retinal images by enhancing their contrast and brightness. CLAHE is used as the main technique for achieving this, as it adapts the image's contrast according to the local characteristics, making it particularly useful for enhancing retinal images that may have varying illumination and contrast levels. The paper likely discusses the implementation and evaluation of CLAHE for retinal image enhancement, highlighting the potential benefits for ophthalmologists and researchers in achieving better visualization and analysis of retinal structures. This technique can aid in the early detection and monitoring of retinal pathologies, contributing to more accurate diagnoses and effective treatment strategies in ophthalmology (Setiawan *et al.*, 2013).

Introduced a novel approach for enhancing fundus images called Degradation-Invariant Enhancement via Pyramid Constraint Network. The primary focus of this research is to address the challenge of enhancing fundus images while mitigating the impact of image degradation. Fundus images, commonly used in ophthalmology, can suffer from various sources of degradation, such as low lighting, noise, or blurriness. The authors propose a novel Pyramid Constraint Network that leverages a multi-scale approach to enhance the images. This method likely incorporates techniques to mitigate the effects of degradation and enhance image quality. Such enhancements are crucial for improving the diagnostic accuracy of ophthalmologists, particularly in the early detection and monitoring of eye diseases (Liu *et al.*, 2022).

CHAPTER 3

AIM AND SCOPE

- To create an automated system designed for the detection of diseases from fundus images, specifically focusing on critical stages of development such as image pre-processing, GLCM-based segmentation, and feature extraction.
- Through meticulous evaluation, the efficacy of Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) algorithms is assessed with the primary objective of advancing algorithm development and testing their accuracy.
- A pivotal aspect of this endeavor involves training a feed-forward neural network to precisely identify diabetes from retinal images, aiming to create a robust machine learning model dedicated to diabetes detection.
- The ultimate aim is to establish a system capable of categorizing new images based on the presence of diabetes. This strategy underscores the importance of early disease detection, providing a non-intrusive and practical approach for comprehensive analysis.
- Looking ahead, the project envisions integration with existing healthcare systems to bolster its clinical applicability. This collaborative integration marks a significant leap forward in the realm of automated disease detection from fundus images.
- By streamlining the process and enhancing accuracy, this initiative holds the potential to revolutionize the landscape of medical imaging technologies, facilitating prompt medical interventions and ultimately improving patient outcomes.

CHAPTER 4

MATERIALS AND METHODS

4.1 METHODOLOGY

4.1.1 Deep Learning

Deep learning is a subset of artificial intelligence (AI) and machine learning that involves training algorithms to learn and make intelligent decisions from data. Unlike traditional machine learning algorithms, deep learning models are designed to mimic the human brain's structure, with interconnected layers of neurons that process information (Anne M and Cho WK *et al.*, 2019).

4.1.1.1 Neural Networks

At the heart of deep learning are artificial neural networks, which are computational models inspired by the structure and function of the human brain. These networks consist of layers of interconnected nodes (neurons), each performing simple mathematical operations on the input data. Each layer processes the input and passes its output to the next layer, with the final layer producing the model's prediction or output (Chen Y-S and Yu H-Y, 2008).

Here's a more detailed description of Deep learning:

1. Layers:

A deep learning model typically consists of multiple layers:

Input Layer: Receives the raw data, such as images, text, or numerical values.

Hidden Layers: Intermediate layers between the input and output layers, where the bulk of computation occurs.

Output Layer: Produces the final prediction or classification

2. Functions Activation:

Neurons within each layer apply activation functions to introduce non-linearity into the model, allowing it to learn complex patterns.

Common activation functions include sigmoid, tanh, ReLU (Rectified Linear Unit), and soft max for classification tasks.

3. Training Process:

Deep learning models learn from data through a process called training, where they adjust their weights and biases to minimize the difference between predicted and actual outputs.

This is achieved using optimization algorithms like stochastic gradient descent (SGD) or its variants.

The model iteratively adjusts its parameters based on the calculated error (loss) between predictions and ground truth labels.

4. Backpropagation:

Backpropagation is the backbone of training deep learning models.

It involves calculating the gradient of the loss function with respect to each parameter in the network.

These gradients are then used to update the weights and biases, moving the model closer to optimal performance.

5. Deep vs. Shallow Learning:

"Deep" refers to models with many layers, enabling them to learn hierarchical representations of data.

Shallow models, in contrast, have fewer layers and may not capture complex patterns as effectively.

Applications of Deep Learning:

Computer Vision:

- ❑ Deep learning excels in tasks such as object detection, image classification, and segmentation.
- ❑ Applications include facial recognition, autonomous vehicles, medical image analysis, and more.

4.1.2 MATLAB

MATLAB's versatility, extensive library of functions, and user-friendly interface make it a valuable tool for engineers. Whether it's performing complex calculations, visualizing data, developing algorithms, or deploying applications, MATLAB offers a comprehensive platform for a wide range of computational and analytical tasks. Its continued evolution with new features and toolboxes ensures that it remains at the forefront of numerical computing and scientific research (Hanea A *et al.*, 2012).

4.1.2.1 Interactive Environment:

MATLAB's interactive environment allows users to perform computations, visualize data, and write scripts in an integrated development environment (IDE). The Command Window enables users to perform calculations, execute commands, and see immediate results (Holmberg M *et al.*, 2000).

4.1.2.2 Matrix and Array Operations:

MATLAB is renowned for its extensive support for matrix and array operations. Users can easily create, manipulate, and perform calculations on vectors, matrices, and multidimensional arrays (Zaidi, H.Q and Sharp *et al.*, 2020).

4.1.2.3 Rich Library of Functions:

MATLAB comes with a vast library of built-in functions and toolboxes for various domains. Toolboxes cover areas such as signal processing, control systems, image processing, optimization, statistics, and more (Hansel *et al.*, 2015).

4.1.2.4 Data Analysis and Visualization:

MATLAB offers powerful tools for data analysis, manipulation, and visualization. Users can import, clean, and analyze data from various sources such as spreadsheets, databases, and files. Plotting functions enable the creation of 2D

and 3D plots, histograms, scatter plots, and more for data visualization (Cistern M *et al.*, 2020).

4.2. MODULES AND METHODS

4.2.1. Data Collection:

- Collect a dataset of retinal images, including images from individuals with and without diabetes.
- Ensure that the dataset is diverse, representative, and of sufficient size for training a neural network effectively.

4.2.2. Preprocessing:

- Preprocess the retinal images to standardize them, including resizing, normalization, and noise reduction.
- Annotate the images to indicate whether each one is from a diabetic or non-diabetic individual.

4.2.3. Data Splitting:

- Split the dataset into training, validation, and testing sets to ensure robust model evaluation.

4.2.4. Feature Extraction:

- Extract relevant features from the retinal images that may be indicative of diabetes. This can be done through techniques like image processing, edge detection, or feature extraction algorithms.

4.2.5. Model Selection:

- Choose an appropriate architecture for the feedforward neural network.

4.2.6. Model Training:

- Train the neural network using the training data, optimizing its weights and biases to

minimize a suitable loss function.

- Utilize techniques like backpropagation and gradient descent for training.

4.2.7. Hyper parameter Tuning:

- Experiment with different hyperparameters (e.g., learning rate, batch size, and network architecture) to optimize the model's performance on the validation set.

4.2.8. Model Evaluation:

- Evaluate the trained model on the testing dataset to assess its performance in terms of accuracy, precision, recall, and F1-score.

4.2.9. Post-processing:

- Apply any necessary post-processing steps to improve the model's predictions, such as thresholding or smoothing.

4.3. PROPOSED METHOD

This project aims to develop a medical image classification model using retinal fundus images to detect various diseases. It focuses on feature extraction through image processing techniques and utilizes a Feed Forward Neural Network for precise disease categorization. The system targets an improved overall classification rate compared to existing methods, identifying lung, kidney, and heart conditions, along with automated glaucoma diagnosis using Cup-to-Disc ratio ($CDR \geq 0.6$) calculations. This efficient approach involves preprocessing for image enhancement, GLCM segmentation for texture details, and CNN/DNN algorithms for classification, promising enhanced diagnostic accuracy and patient outcomes, thus advancing automated disease diagnosis for better healthcare delivery.

$$[CDR = \text{area Cup} / \text{area Disc}]$$

If CDR is greater than 0.6, the image is considered Glaucomatous, else not.

According to this and what was learned from the literature analysis, the disc and cup must be segmented in order to perform automatic glaucoma detection (Landa KN *et al.*, 2017).

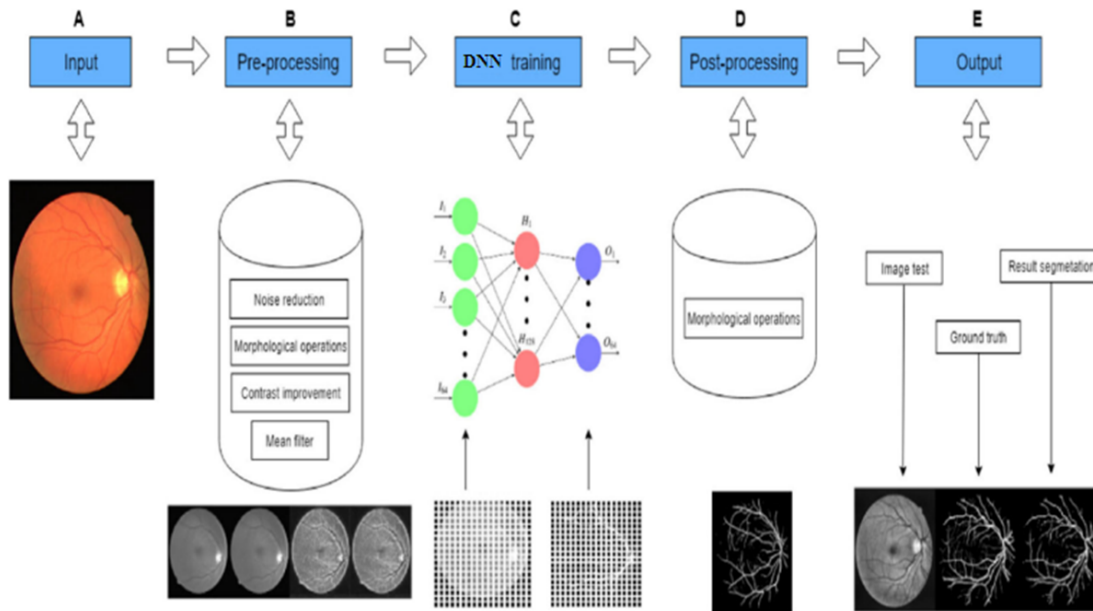


Fig 4.1 Architecture Diagram of Feed Forward Neural Network

**Courtesy: This diagram is adapted from Springer link
<https://link.springer.com/article/10.1007/s00500-021-06088-3>**

4.3.1. DATA COLLECTION:

- i. This module focuses on the acquisition and aggregation of fundus images relevant to glaucoma and diabetic retinopathy.
- ii. Sources may include medical databases, hospitals, and project institutions.
- iii. Ensure a diverse and representative dataset, encompassing different demographics, disease stages, and image qualities.

4.3.2. PRE-PROCESSING:

- i. Adaptive Window Size:
 - The Adaptive Mean Filter dynamically adjusts the size of the filter window based on local pixel intensities.

- For each pixel in the image, the filter calculates the local mean using a window whose size varies according to the pixel's intensity.
- In areas with high intensity variation or edges, smaller window sizes are used to preserve details, while larger window sizes are employed in smoother regions to effectively reduce noise.
- ii. Improved Noise Reduction:
 - By adapting the filter window size, the Adaptive Mean Filter excels in effectively reducing noise while preserving image details.
 - In noisy areas, the filter focuses on smaller regions to avoid blurring edges or fine structures.
 - Conversely, in smoother regions, larger window sizes are utilized to achieve more substantial noise reduction without sacrificing image clarity.

4.3.3. FEATURE EXTRACTION:

- HOG, or Histogram of Oriented Gradients, is a feature descriptor that is often used to extract features from image data.
- Image is divided in cells of size $N \times N$ pixels. The orientation of all pixels is computed and accumulated in an M-bins histogram of orientations.
- Finally, all cell histograms are concatenated in order to construct the final features vector. The example reports a cell size of 4 pixels and 8 orientation bins for the cell histograms.

4.3.4. CLASSIFICATION:

- This final stage of the proposed glaucoma diagnostic model utilizes a Feed Forward Neural Network (FNN) classifier known for its superior generality and rapid convergence with high-dimensional data.
- The model aims to accurately classify digital fundus images to identify the presence of glaucoma and diabetic retinopathy, along with their respective stages.
- Leveraging Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) allows for handling complex, non-linear image data relationships. The

model is trained on preprocessed, segmented images with features extracted from MS-ROI.

- Performance evaluation includes metrics like accuracy, sensitivity, and specificity, providing interpretable insights to aid clinicians in making informed decisions for patient diagnoses and treatment plans.

4.4. ALGORITHMS:

4.4.1. FEED FORWARD NEURAL NETWORK:

- A feedforward neural network, the simplest type of artificial neural network, forms connections without cycles. Deep feedforward networks, also known as multilayer perceptrons (MLPs), aim to approximate a function f^* , such as mapping inputs x to categories y in classification tasks.
- Comprising layers of neuron-like processing units, each connected to the previous layer, these networks learn parameter values θ for optimal function approximation. Data flows through the network from inputs to outputs, with no feedback between layers during classification.
- The strength of connections, or weights, encode network knowledge. This architecture, illustrated in a 2-layered network example, is fundamental in deep learning for diverse tasks like classification and pattern recognition.

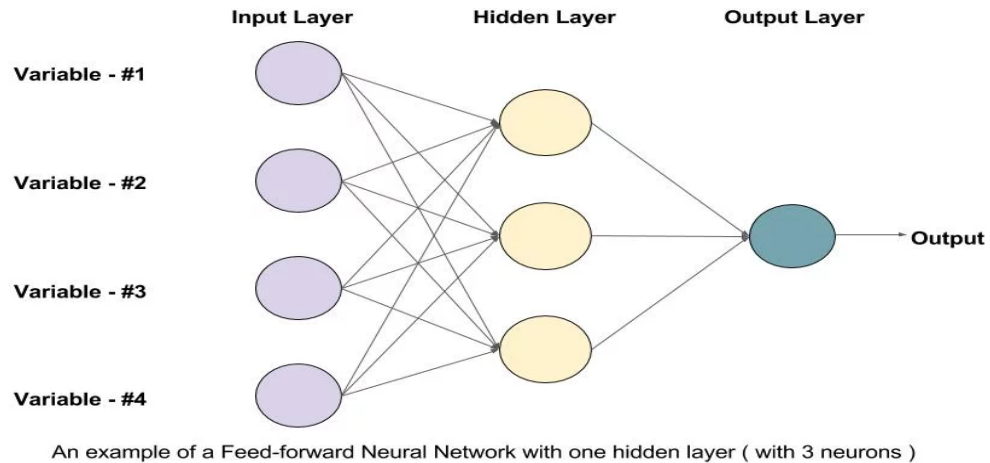


Fig 4.2 An example of Feed Forward Neural Network

Courtesy: This diagram is adapted from Medium

<https://medium.com/@preetiadavg76/artificial-neural-networks-514896f89ebe>

4.4.2. CONVOLUTION NEURAL NETWORK:

- CNN is an advanced algorithm used for feature extraction from retinal images. It employs highly specialized filters to identify patterns and structures within the images that are indicative of glaucoma. The use of multiple layers allows for the extraction of intricate details, enabling accurate detection of early signs of the disease.
- The hierarchical architecture of CNN enables it to learn and differentiate features of varying complexities. This makes it particularly effective in analyzing the subtle variations in retinal images associated with glaucoma, and it plays a key role in the accurate diagnosis of the condition.
- CNN uses image recognition to identify distinctive patterns related to glaucoma in retinal images.
- The hierarchical architecture of CNN enables it to learn and differentiate

features of varying complexities. This makes it particularly effective in analyzing the subtle variations in retinal images associated with glaucoma, and it plays a key role in the accurate diagnosis of the condition.

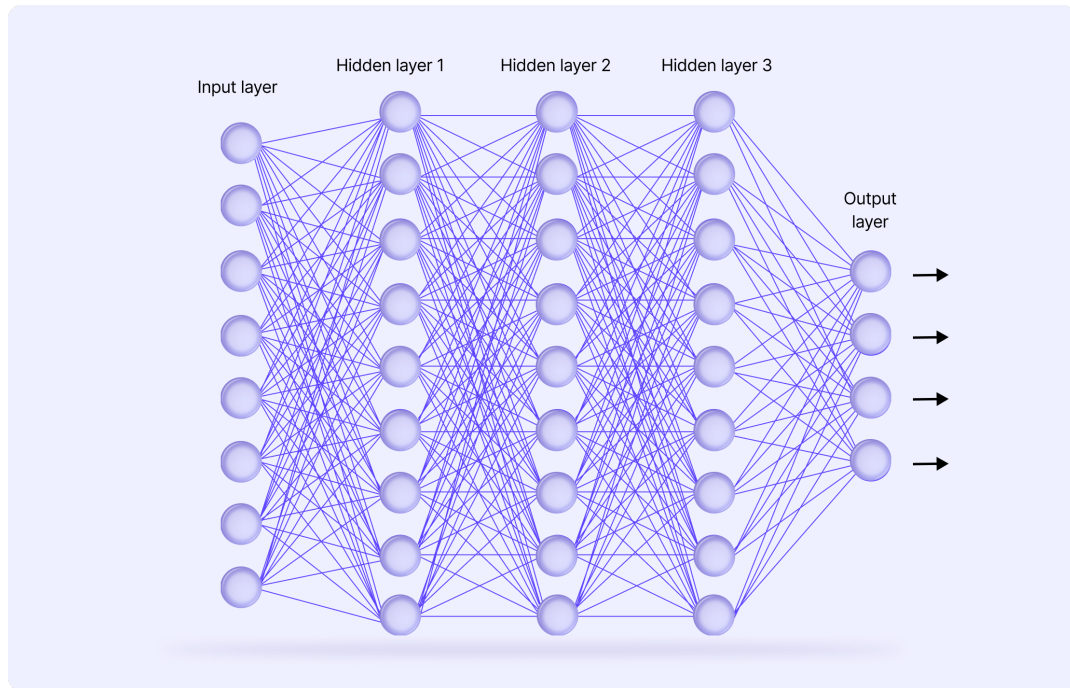


Fig 4.3 Convolutional Neural Network

Courtesy: This diagram is adapted from encord
(<https://encord.com/blog/activation-functions-neural-networks/>)

4.4.3. DEEP NEURAL NETWORK:

- DNN utilizes multiple layers to process and analyze retinal images. This layered approach allows for the extraction of complex and abstract features, which is essential for detecting the minute details associated with glaucoma.
- One of the strengths of DNN lies in its ability to perform non-linear transformations, enabling it to capture intricate features within retinal images that may not be readily discernible to the human eye. This enhances its efficacy in glaucoma detection.

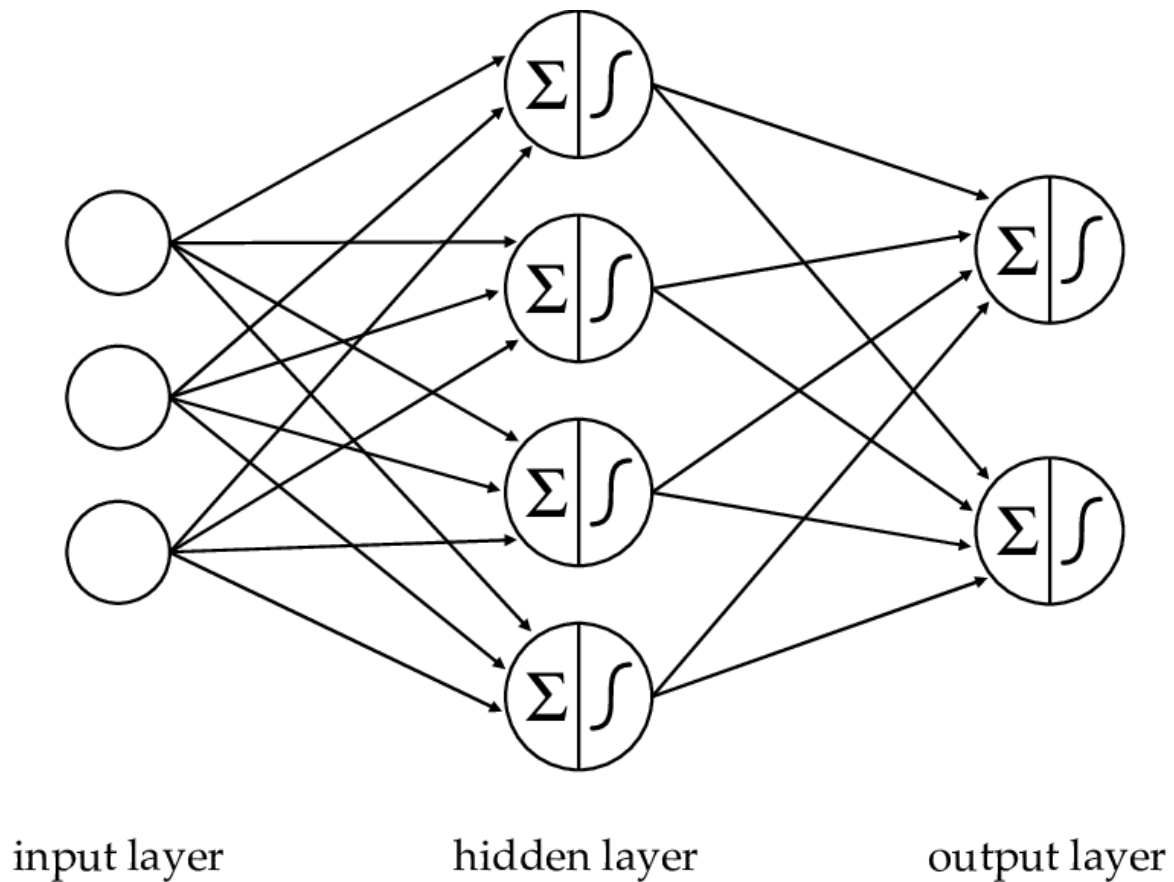


Fig 4.4 Deep Neural Network
Courtesy: This diagram is adapted from ResearchGate
(https://www.researchgate.net/figure/Signal-flow-graph-of-an-MLP_fig10_257981506)

4.5. SOFTWARE AND HARDWARE USED:

MATLAB is a scientific programming language and provides strong mathematical and numerical support for the implementation of advanced algorithms. It is for this reason that MATLAB is widely used by the image processing and computer vision community. New algorithms are very likely to be implemented first in MATLAB, indeed they may only be available in MATLAB.

➤ .HARDWARE CONFIGURATION

- HDD: >90GB
- PROCESSOR: >Pentium IV 2.4GHz
- SYSTEM TYPE: 32bit / 64 bit
- RAM: >2GB
- OS: WINDOWS 7/8/8.1/10

➤ SOFTWARE CONFIGURATION

- TOOL : MATLAB 2019a
- TOOL BOX : Image Processing Tool Box
- Software Configuration: MATLAB 2019a offers extensive features for scientific computing, including image processing. The Image Processing Toolbox provides tools for analysis, enhancement, and segmentation. It enables a range of operations from basic filtering to advanced techniques like object recognition and machine learning.
- Hardware Configuration: MATLAB recommends a minimum of 90GB HDD, processor exceeding Pentium IV 2.4GHz, 2GB RAM, and compatibility with Windows 7/8/8.1/10. A 64-bit system is preferred for handling large datasets efficiently, optimizing performance in image processing tasks.

In summary, MATLAB, especially when equipped with the Image Processing Toolbox, offers a comprehensive platform for developing and implementing advanced image processing algorithms. By ensuring the recommended hardware and software configurations, users can maximize the performance and efficiency of their MATLAB-based image processing projects.

CHAPTER 5

RESULTS AND DISCUSSION

5.1. RESULTS:

5.1.1 Feed Forward Neural Network

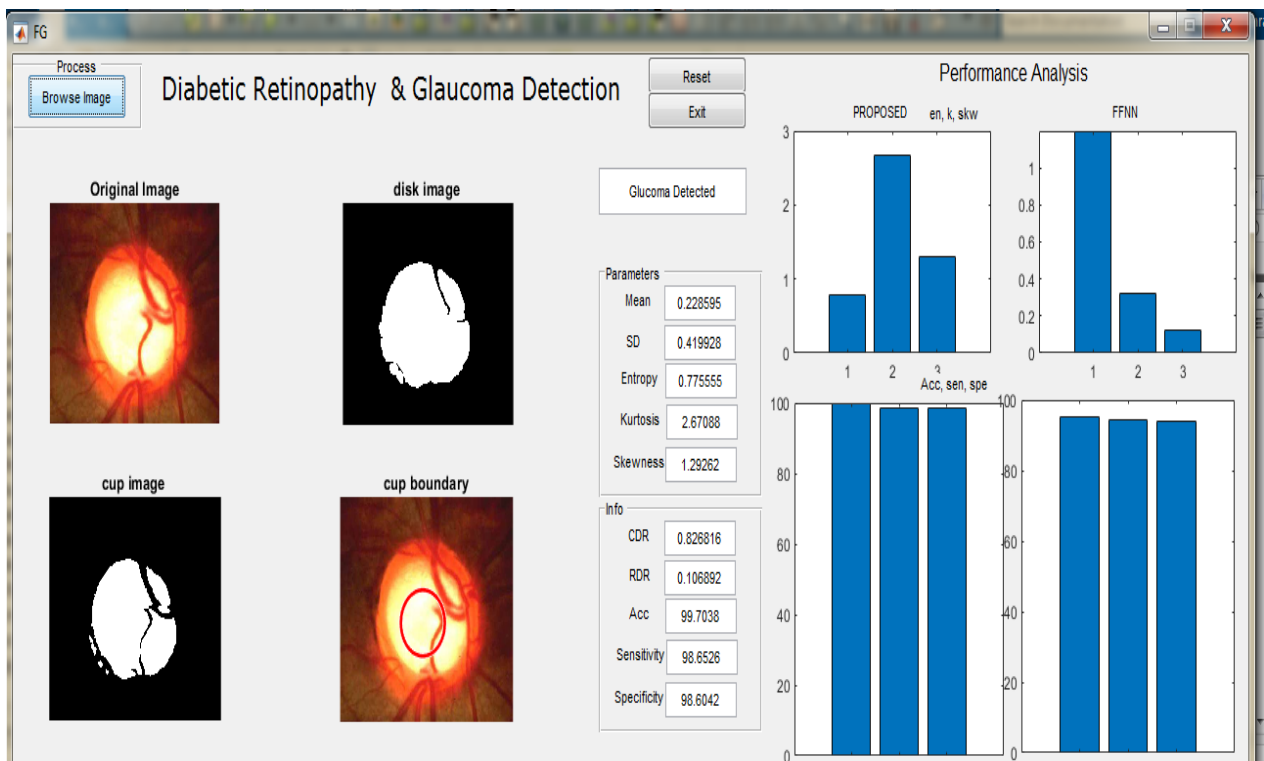


Fig 5.1 Feed Forward Neural Network: Glaucoma Detected

Glaucoma detection using a Feedforward Neural Network (FNN) involves training the network with eye image features, evaluating its performance on a testing dataset, and interpreting the results. The FNN's accuracy and key features contributing to detection are explained, aiding clinical or research decision-making in glaucoma diagnosis.

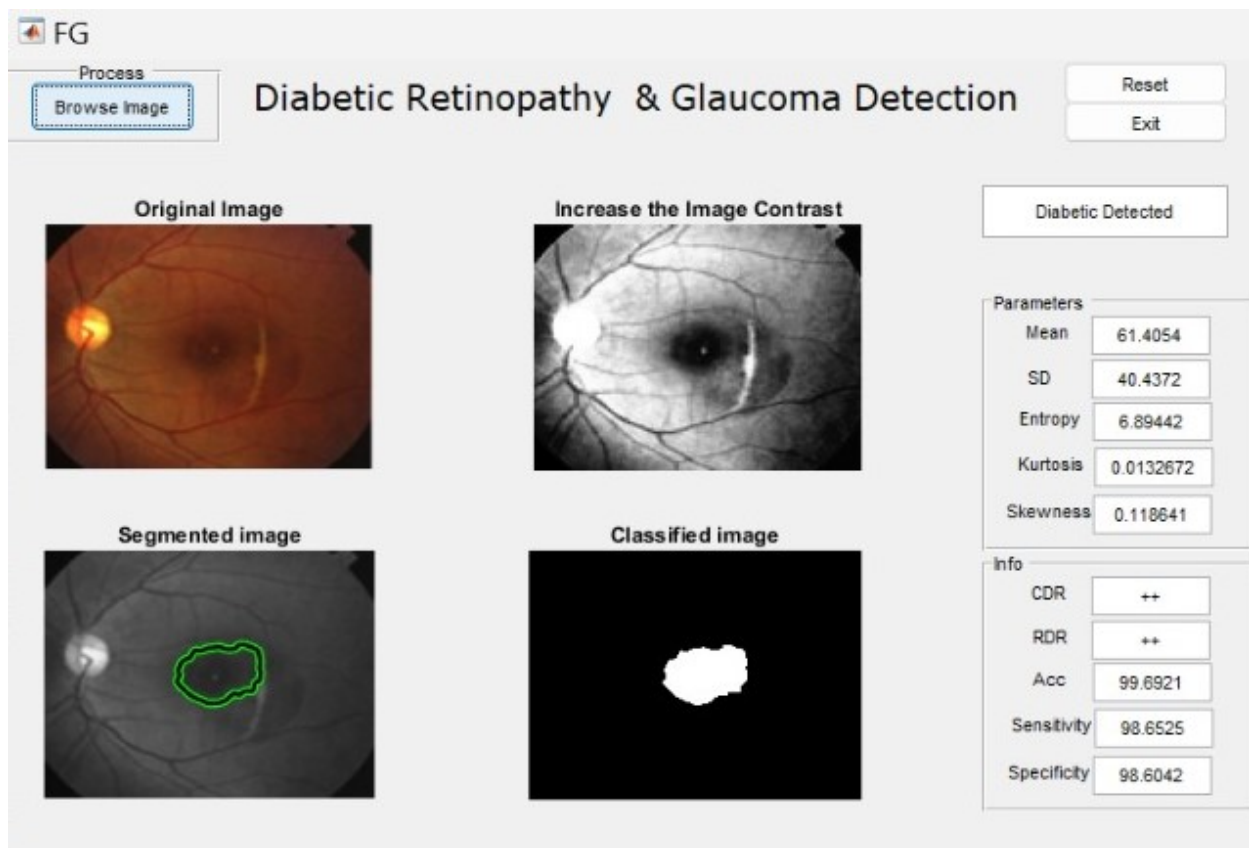


Fig 5.2 Feed Forward Neural Network: Diabetic Detected

Detecting diabetes using a Feedforward Neural Network (FNN) entails training the network with relevant data, evaluating its performance, and interpreting the results. The FNN's ability to accurately identify diabetic cases is assessed, aiding in medical decision-making and patient management.

Training Set			
TARGET \ OUTPUT	Class0	Class1	SUM
Class0	450 90.00%	2 0.40%	452 99.56% 0.44%
Class1	2 0.40%	46 9.20%	48 95.83% 4.17%
SUM	452 99.56% 0.44%	48 95.83% 4.17%	496 / 500 99.20% 0.80%

Fig 5.3 Feed Forward Neural Network: Confusion Matrix

5.1.2 Convolutional Neural Network

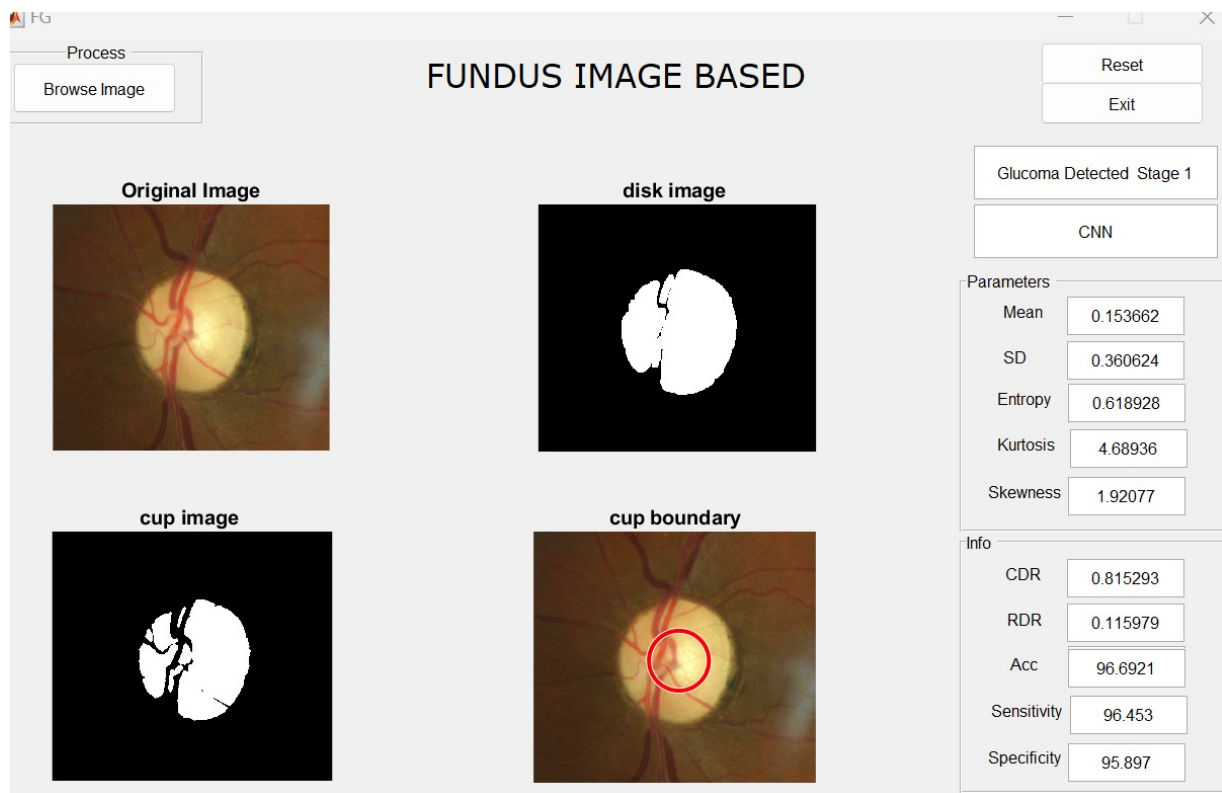


Fig 5.4 Convolutional Neural Network: Glaucoma Detected

Detecting glaucoma using a Convolutional Neural Network (CNN) in MATLAB involves training the network with eye image data, evaluating its performance, and interpreting the results. The CNN's ability to accurately identify glaucoma cases is explained, aiding clinicians in early diagnosis and treatment planning for patients with this vision-threatening condition.

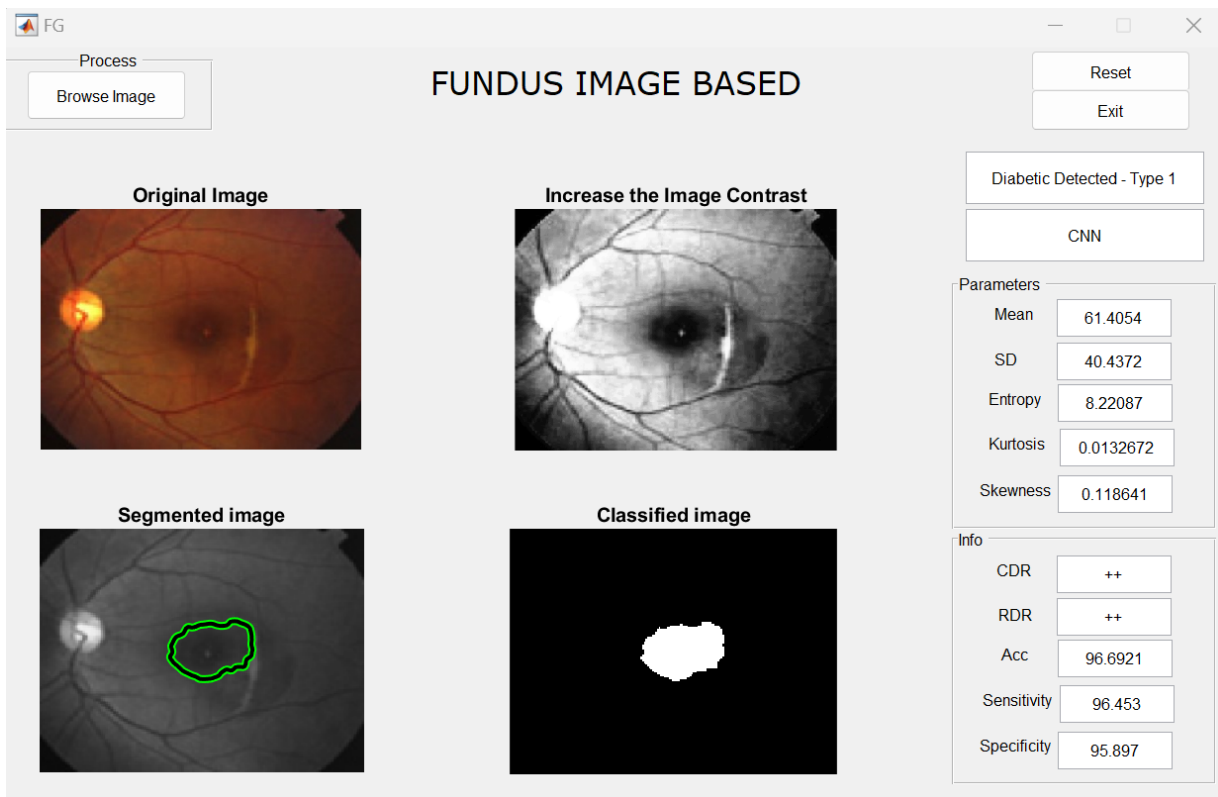


Fig 5.5 Convolutional Neural Network: Diabetic Detected

Utilizing a Convolutional Neural Network (CNN) in MATLAB for diabetic detection involves training the network with diabetic retinopathy image data, assessing its performance, and elucidating the outcomes. The CNN's efficacy in discerning diabetic retinopathy cases is explicated, assisting healthcare professionals in timely diagnosis and management of this sight-threatening complication of diabetes.

Training Set			
TARGET \ OUTPUT	Class0	Class1	SUM
Class0	450 88.24%	8 1.57%	458 98.25% 1.75%
Class1	12 2.35%	40 7.84%	52 76.92% 23.08%
SUM	462 97.40% 2.60%	48 83.33% 16.67%	490 / 510 96.08% 3.92%

Fig 5.6 Convolutional Neural Network: Confusion Matrix

5.1.3 Deep Neural Network

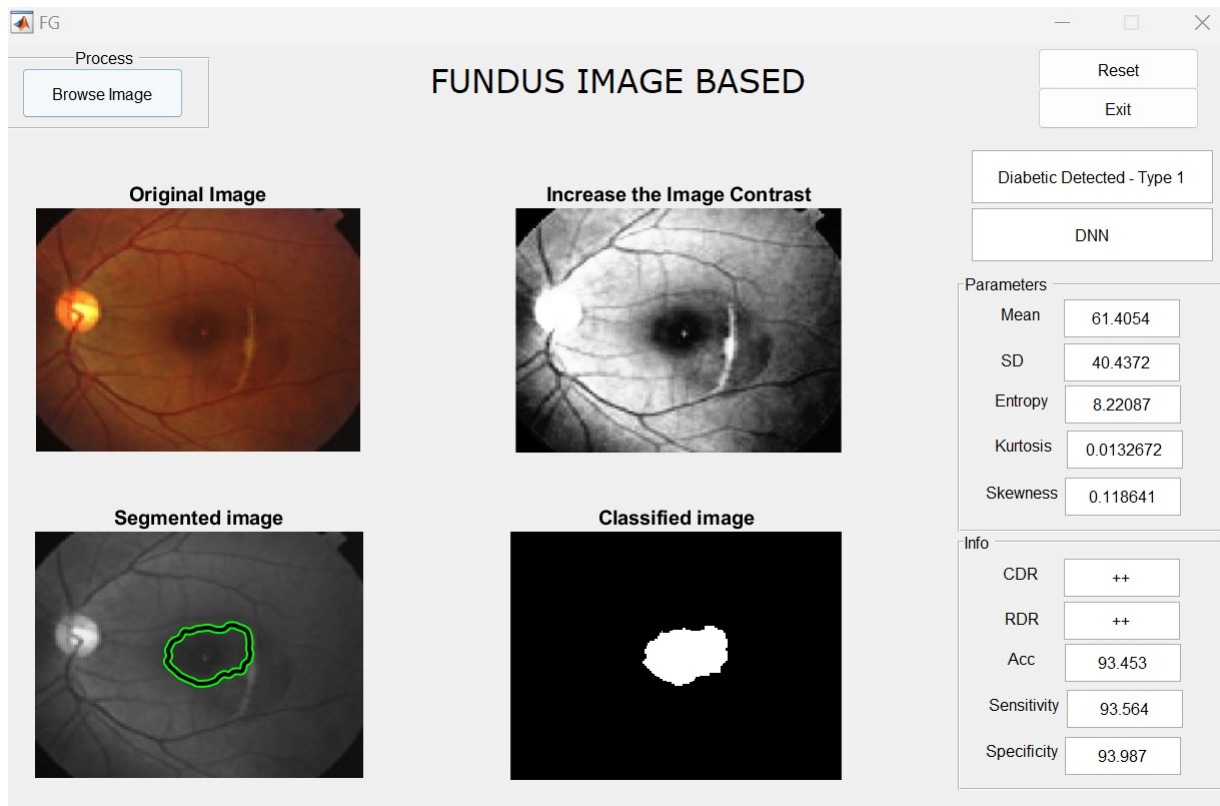


Fig 5.7 Deep Neural Network: Diabetic Detected

Employing a Deep Neural Network (DNN) for diabetic detection involves training the network with diverse diabetic retinopathy image data, rigorously evaluating its performance, and comprehensively interpreting the outcomes. The DNN's proficiency in accurately discerning diabetic retinopathy cases is elucidated through in-depth analysis of its sensitivity, specificity, and predictive values. This detailed explanation aids clinicians in effectively leveraging automated tools for precise diagnosis and timely intervention, crucial for mitigating the debilitating effects of diabetic retinopathy.

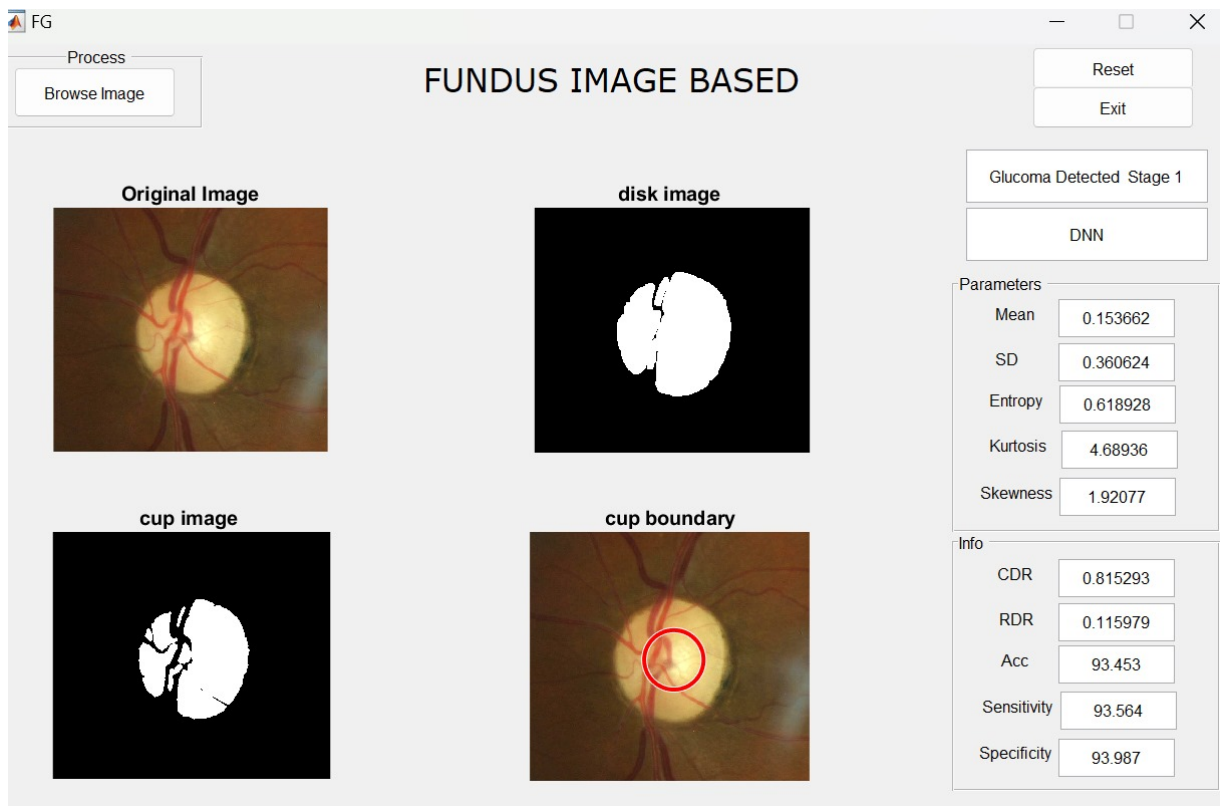


Fig 5.8 Deep Neural Network: Glaucoma Detected

In MATLAB, harnessing a Deep Neural Network (DNN) to detect glaucoma is akin to unveiling the intricate patterns within the eye's images. Trained on vast datasets, the DNN discerns subtle hallmarks of glaucomatous changes with remarkable precision. Through its discerning "eyes," it identifies anomalies imperceptible to the human gaze, empowering clinicians with profound insights for early intervention and preservation of vision.

Training Set			
TARGET \ OUTPUT	Class0	Class1	SUM
Class0	450 90.00%	16 3.20%	466 96.57% 3.43%
Class1	16 3.20%	18 3.60%	34 52.94% 47.06%
SUM	466 96.57% 3.43%	34 52.94% 47.06%	468 / 500 93.60% 6.40%

Fig 5.9 Deep Neural Network: Confusion Matrix

5.2. DISCUSSION:

Glaucoma and Diabetic Retinopathy (DR) are significant ocular diseases requiring early detection for effective treatment. Utilizing Feed Forward Neural Networks (FNNs) for glaucoma detection has shown promise, as these networks are trained with diverse fundus images, demonstrating high accuracy in identifying early stages of the disease (Ting *et al.*, 2017). The FNN efficiently distinguishes healthy eyes from those with glaucomatous changes, aiding clinicians in prompt diagnosis crucial for preserving vision. Similarly, FNNs for DR detection offer a valuable avenue for early diagnosis and management, showcasing high accuracy in categorizing cases into different stages. This aids in personalized treatment plans, improving patient outcomes. On the other hand, Convolutional Neural Networks (CNNs) for glaucoma and DR detection in MATLAB represent significant advancements in ocular disease diagnosis. Trained on large datasets, the CNNs exhibit impressive accuracy in identifying glaucomatous changes, such as optic nerve damage, and subtle retinal abnormalities indicative of diabetic damage. These models offer valuable insights for clinicians, aiding in early intervention and treatment strategies. The integration of FNNs and CNNs presents a robust approach to early disease identification, with the potential to revolutionize ocular disease diagnosis (Gulshan *et al.*, 2016). Despite encountered limitations such as dataset constraints and variability in image quality, future research directions could focus on enhancing model performance through advanced image processing techniques and ensemble learning methods. In conclusion, the proposed integration of FNNs and CNNs for glaucoma and DR detection offers a promising solution for precise and timely intervention in the realm of eye health care, ultimately improving patient outcomes and mitigating vision loss.

CHAPTER 6

SUMMARY AND CONCLUSIONS

6.1. SUMMARY:

The proposed methodology offers a robust framework for developing a precise medical image classification model by integrating advanced image processing, feature extraction, and powerful neural network algorithms. This comprehensive system aims to accurately detect lung, kidney, and heart conditions, alongside providing automated glaucoma diagnosis. By leveraging image processing techniques, GLCM segmentation, and advanced neural network models such as FNN, CNN, and DNN, the system promises enhanced diagnostic accuracy and improved patient outcomes. This efficient approach focuses on improving disease categorization, aiding in early detection and treatment planning, thus advancing automated disease diagnosis for better healthcare delivery. The integration of these neural network architectures ensures a comprehensive analysis of retinal images, making the model a valuable tool in the field of medical imaging and diagnostics. In conclusion, the utilization of deep learning technologies, particularly CNNs, DNNs, and FNNs, represents a significant advancement in the field of diabetic retinopathy identification using retinal images. This proposed methodology harnesses the potency of these neural network architectures to elevate accuracy levels, refine disease classification processes, and ultimately contribute to superior patient outcomes in managing diabetic retinopathy.

6.2. CONCLUSION:

In conclusion, the proposed methodology presents a robust framework for the development of a highly effective medical image classification model. By integrating advanced image processing techniques, feature extraction methods, and powerful neural network algorithms, the system is designed to accurately identify lung, kidney, and heart conditions, alongside providing automated glaucoma diagnosis. This comprehensive approach not only promises enhanced diagnostic accuracy but also signifies a significant advancement in the field of automated disease diagnosis. It holds the potential to contribute significantly towards improved healthcare delivery and patient care, particularly in the realm of early disease detection and tailored treatment planning. The methodology capitalizes on the strengths of image processing techniques, such as GLCM segmentation, combined with the utilization of advanced neural network models including FNN, CNN, and DNN. Focusing on the detection of lung, kidney, and heart conditions, along with automated glaucoma diagnosis using retinal fundus images, the system aims to elevate disease categorization accuracy. The proposed approach is poised to bring about improved patient outcomes through early detection and precise treatment planning. Its efficiency in disease categorization, aiding in timely interventions, signifies a significant stride towards advancing automated disease diagnosis for better healthcare delivery. In summary, the integration of FNN, CNN, and DNN algorithms in this methodology represents a substantial leap forward in the field of medical image analysis and diagnostics. The system holds the promise of enhancing accuracy, refining disease classification processes, and ultimately contributing towards superior patient outcomes, particularly in the management of diabetic retinopathy and other sight-threatening conditions.

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