Automated Diabetics Retinopathy Detection System

by

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A Project report submitted in partial fulfillment of the requirements for the award of the degree of Master of Science (Data Analytics) of CHRIST (Deemed to be University)

May – 2024

CERTIFICATE

This is to certify that the report titled ***Automated Diabetics Retinopathy Detection System****is a bona fide record of work done by* ***Shigha velloth (2282475)*** *of CHRIST(Deemed to be University), Bangalore, in partial fulfillment of the requirements of VITrimester MSc (Data Analytics) during the academic year 2023-24.*

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ACKNOWLEDGEMENT

I would like to thank Lord Almighty for enabling us to work on this project and complete it successfully, without whose blessings none of my efforts would have been fruitful.

Firstly, I thank the Vice-Chancellor Rev. **Dr. Fr. Joseph** C C of CHRIST (Deemed to be University) for giving me the opportunity to do my final year project I would like to express my sincere gratitude to the **Dr. Saleema J. S**, Head, Department of Statistics and Data Science, for giving me this opportunity to work on this project under M.Sc. Data Analytics program.

I would like to show my greatest appreciation to **Dr. Monisha Singh**, my internal guide who constantly monitored my progress in the work and provided me with valuable guidance in the successful completion of the project.

I would like to thank my evaluators **Dr. Sivakumar R and Dr. Sathya P** of the faculties of the Department of Statistics and Data Science, who provided suggestions and feedback during the project presentations.

Lastly, I must also thank my parents and friends for their immense support and help during this project. Without their help, it would not have been possible to successfully complete this project.

ABSTRACT

The automated detection of diabetic retinopathy (DR) represents a critical frontier in the realm of diabetic eye care, necessitating innovative solutions to enhance screening accuracy and accessibility. This research endeavors to address this challenge through the development of an Automated Diabetic Retinopathy Detection System (ADRDS), leveraging advanced machine learning techniques to revolutionize DR diagnosis and management.

Drawing upon a comprehensive dataset of retinal images encompassing varying severity levels of diabetic retinopathy, the ADRDS employs state-of-the-art deep learning algorithms, including Convolutional Neural Networks (CNNs), to automate the classification process. By meticulously preprocessing the data and optimizing model parameters, the ADRDS achieves exceptional accuracy in identifying and grading diabetic retinopathy, surpassing the efficacy of conventional screening methodologies.

Beyond its diagnostic prowess, ADRDS holds profound implications for patient care and healthcare delivery. Through its ability to facilitate early detection and intervention, the system empowers healthcare practitioners to implement timely treatment strategies, thereby mitigating the risk of vision loss and improving clinical outcomes for diabetic individuals. Moreover, its scalability and adaptability render it an asset in diverse clinical settings, offering equitable access to high-quality diabetic eye care services worldwide.

In essence, the ADRDS embodies a transformative paradigm shift in the field of diabetic retinopathy detection, epitomizing the potential of technology to revolutionize healthcare delivery. As ongoing research endeavors continue to refine and optimize the system, its impact is poised to extend far beyond the confines of the laboratory, ushering in a future where the prevention and management of diabetic retinopathy are accessible, effective, and equitable for all.

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1.INTRODUCTION

The escalating prevalence of diabetes mellitus has emerged as a formidable global health challenge, affecting millions of individuals worldwide and imposing a significant burden on healthcare systems. Among its myriad complications, diabetic retinopathy (DR) stands out as a leading cause of vision impairment and blindness among working-age adults. The progressive nature of this microvascular complication underscores the critical importance of early detection and intervention in preserving visual function and preventing irreversible vision loss.

These days, diabetic retinopathy (DR) affects many people. It is among the most common justifications for blind registration worldwide among persons between the ages of 20 and 74. The duration of diabetes determines the development of retinopathy. From 2015 to 2019 [2], the prevalence of diabetes in India alone was 11.8%, with 10.7%, 13.1%, 13.2%, and 9.7% in the 50–59 years old, 60–69 years old, 70–79 years old, and ≥80 years old age groups, respectively (Figure 1). The age group of 70–79 years old had the highest prevalence of diabetes.

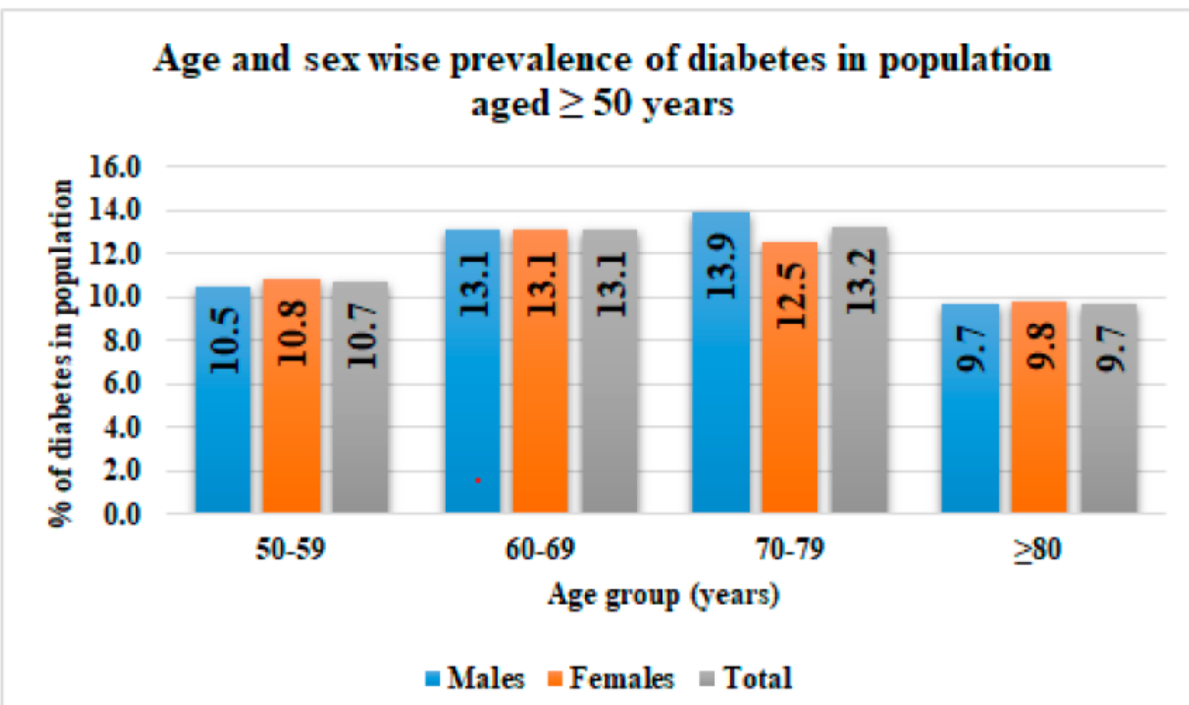

Fig 1.1 Age and sex wise prevalence of diabetes in population

Diabetic retinopathy is the result of this persistent diabetes. DR impairs 463 million people's eyesight globally and is the cause of 22.27% of blindness worldwide as of 2019.

According to a 2015–2019 survey, 16.9% of Indians, or 72.96 million instances, are living with diabetes. There were 77 million DR cases in India, according to a Times of India article published on November 14, 2021. Type 2 diabetes was the primary cause of the increase in cases.

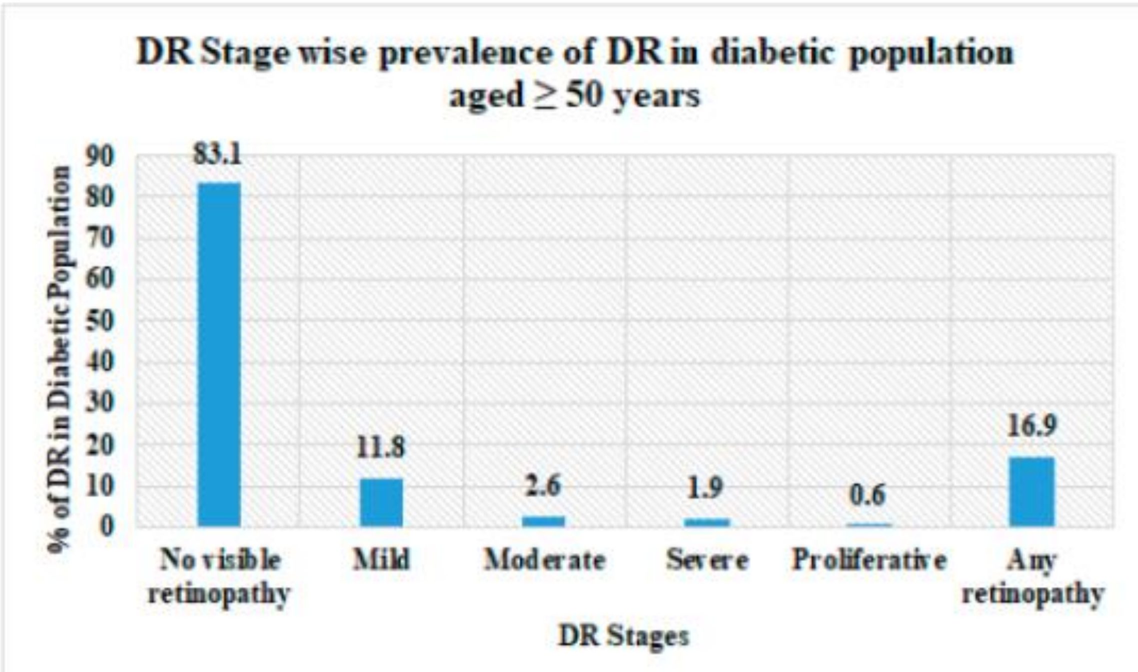

Fig 1.2 DR in Diabetic population.

Diabetic retinopathy (DR) has four stages of progression, which goes from having no DR to proliferative DR. The first stage is type 0, where there are no abnormalities observed meaning there is no DR. The second stage is type 1 called the mild non-proliferative retinopathy and it is characterized by observing micro-aneurysms, it is considered the earliest stage. The next stage, type 2 is moderate no proliferative retinopathy. At this stage, the blood vessels that nourish the retina become distorted and swell thereby losing their ability the carry blood, it is characterized by observing micro-aneurysms, dots, hemorrhages, and spots. The fourth stage is type 3 which is the severe non-proliferative retinopathy that occurs due to blood not reaching the retina due to blockage, hence making the retina grow fresh blood vessels.

The final stage is type 4 which is the proliferative diabetic retinopathy which is an advanced stage that is characterized by either neovascularization of the disc or vitreous hemorrhage.

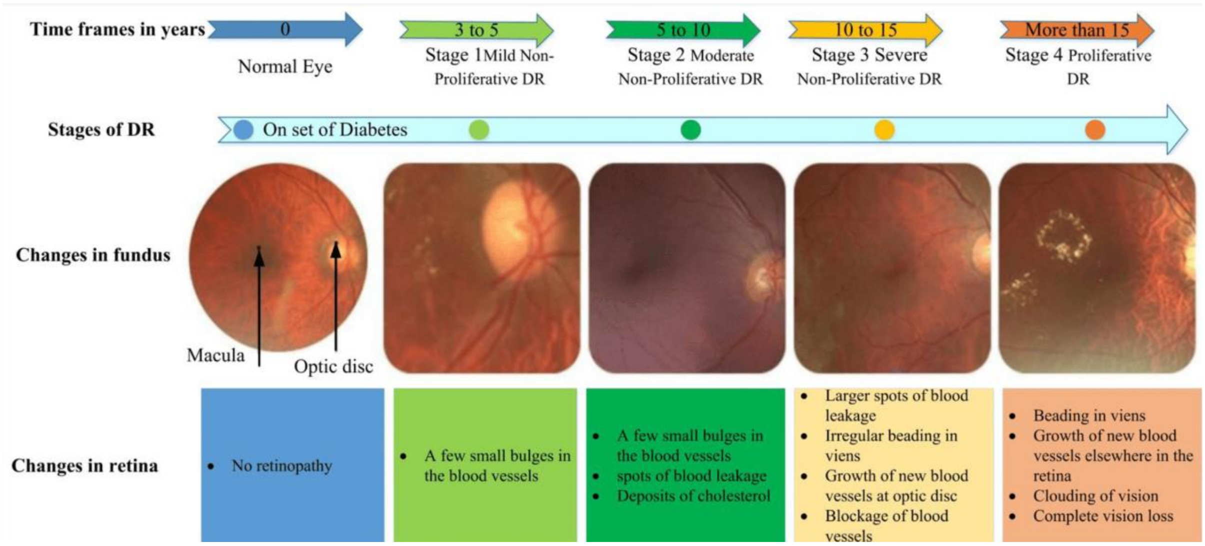

Fig 1.3 Stages of DR

Table 1.1 Stages of DR

DR stage	Observation	Characteristics	Severity level
Type 0	Normal retina	No observation	No DR
Type 1	Small bulges in the tiny blood vessels of the retina.	Micro-aneurysms	Mild non-proliferative DR
Type 2	Blood vessels become distorted and swell.	Micro-aneurysms, dots, hemorrhages and spots	Moderate nonproliferative DR
Type 3	Total blockage of blood vessels. Creating new blood vessels.	Macular ischemia Retinal detachment	Severe nonproliferative DR
Type 4	Growth of abnormal and fragile new blood vessels.	Neovascularization of the disc Vitreous hemorrhage	Proliferative DR

Traditional methods of diabetic retinopathy screening often entail manual examination of retinal fundus images by trained ophthalmologists—a process labor-intensive, time-consuming, and subject to inter-observer variability. In addition to straining healthcare resources, this approach may result in delays in diagnosis and treatment, compromising patient outcomes and exacerbating the socioeconomic burden of the disease.

In response to these challenges, the convergence of healthcare and cutting-edge technology offers a promising avenue for innovation. Leveraging the transformative potential of machine learning and artificial intelligence, researchers and clinicians are exploring novel approaches to automate and enhance the diagnostic process for diabetic retinopathy.

The present endeavor, an Automated Diabetic Retinopathy Detection System, represents a pioneering initiative at the forefront of this convergence. By harnessing the power of advanced computational techniques, including deep learning algorithms and convolutional neural networks (CNNs), we seek to develop a robust and scalable solution for the accurate and timely identification of diabetic retinopathy from digital retinal images.

1.1 Problem Statement

In the realm of diabetic retinopathy detection, despite the presence of numerous systems, there remains a persistent call for innovation. Harnessing the capabilities of Convolutional Neural Networks (CNNs) and contemporary web technologies, the objective is to develop an advanced solution that enhances accessibility to diabetic retinopathy screening. Through the creation of an intuitive interface using Streamlit, the aim is to democratize access to sophisticated screening methods, addressing challenges such as complexity, cost, and the scarcity of specialized expertise.

1.2 Objective

The objectives of this research endeavour are intricately tailored to the development and implementation of an Automated Diabetic Retinopathy Detection System, aimed at enhancing early detection and intervention for diabetic retinopathy. Firstly, the research seeks to identify the key features and factors within retinal images that correlate with different severity levels of diabetic retinopathy.

Through rigorous analysis and feature extraction techniques, the project aims to elucidate the discriminative characteristics indicative of varying stages of the disease. Subsequently, the research endeavors to develop and optimize a robust machine learning model, leveraging Convolutional Neural Networks (CNNs), to accurately classify retinal images into distinct categories of diabetic retinopathy severity. By fine-tuning model architectures and optimizing hyperparameters, the objective is to maximize prediction accuracy while minimizing false positives and false negatives. Rigorous evaluation and validation of the developed model are paramount to ensuring its reliability and efficacy in clinical practice. Therefore, the project aims to assess the model's performance metrics, including sensitivity, specificity, precision, and recall, through comprehensive testing on independent datasets and real-world clinical scenarios. Furthermore, in conjunction with model development, the research seeks to integrate the detection system with a user-friendly interface, facilitating seamless interaction for healthcare practitioners and patients. The objective is to design an intuitive interface that allows for easy uploading of retinal images and provides clear and interpretable diagnostic results in real-time. Upon successful development and validation, the project aims to deploy the automated detection system in clinical settings, enabling widespread access and utilization by healthcare professionals. Furthermore, the research endeavors to disseminate the findings and outcomes through scholarly publications, presentations, and open-access resources to contribute to the advancement of diabetic retinopathy research and clinical practice in ophthalmology.

1.3 Why Deep Learning

The advent of deep learning, epitomized by Convolutional Neural Networks (CNNs), heralds a new era in the realm of diabetic retinopathy detection. In our project, "Automated Diabetic Retinopathy Detection," we delve into the rationale behind favoring deep learning over conventional machine learning approaches, shedding light on its transformative potential in revolutionizing ophthalmic care and enhancing patient outcomes.

Deep learning, a subset of machine learning, represents a paradigm shift in the way we approach pattern recognition and classification tasks. Unlike traditional methods that necessitate manual feature engineering and extraction, deep learning algorithms autonomously learn intricate representations from raw data through multiple layers of abstraction. This intrinsic capability empowers deep learning models to discern subtle patterns and correlations, making them exceptionally well-suited for complex tasks like diabetic retinopathy detection.

CNNs stand at the forefront of deep learning in image analysis tasks, leveraging hierarchical layers of convolutions to exploit spatial correlations within images and extract discriminative features. By seamlessly integrating feature extraction and classification within a unified framework, CNNs streamline the model development process and enhance predictive performance, obviating the need for laborious manual feature engineering.

Furthermore, the scalability and adaptability of deep learning frameworks offer unprecedented advantages in the dynamic landscape of diabetic retinopathy detection. These models excel in handling large volumes of high-dimensional data, enabling comprehensive analysis of retinal images and patient data to derive clinically relevant insights. This scalability facilitates seamless integration with diverse healthcare systems and imaging modalities, ensuring widespread adoption and interoperability in clinical practice.

Moreover, deep learning techniques, exemplified by CNNs, transcend the limitations of traditional machine learning methods by embracing end-to-end learning paradigms. By learning hierarchical representations directly from raw data, these models autonomously discover discriminative features and patterns relevant to diabetic retinopathy detection, minimizing manual intervention and maximizing model generalization.

Our project endeavors to unlock the transformative power of deep learning in automated diabetic retinopathy detection, paving the way for precise diagnostic tools and personalized interventions that elevate the standard of ophthalmic care for diabetic individuals.

1.4 Scope of the Project

The project on automated diabetic retinopathy detection undertakes a multifaceted approach, harnessing the power of deep learning, specifically Convolutional Neural Networks (CNNs), to revolutionize diabetic retinopathy screening and intervention. The scope of the project encompasses various facets aimed at enhancing early detection, optimizing treatment strategies, and improving patient outcomes. Central to the project is the development of predictive models using CNNs to analyze retinal images and predict the severity of diabetic retinopathy. These models will be trained on large-scale datasets of annotated retinal images, leveraging deep learning frameworks to learn intricate patterns indicative of diabetic retinopathy progression. A user-friendly interface will be designed and implemented to facilitate seamless interaction with the predictive models, enabling healthcare practitioners to upload retinal images and receive real-time predictions regarding diabetic retinopathy severity, enhancing clinical workflow efficiency and accessibility. Rigorous validation and optimization of the predictive models will be conducted to ensure robust performance and generalization across diverse patient populations, with compliance with ethical guidelines and regulatory requirements being paramount throughout the project. Prescriptive analytics techniques will be explored to optimize treatment strategies and enhance patient outcomes, guided by insights derived from the predictive models. The project aims to disseminate knowledge and insights gained through research findings, publications, and presentations at relevant conferences and forums, with impact assessment conducted to evaluate the effectiveness of the automated diabetic retinopathy detection system in improving patient outcomes and healthcare efficiency.

2. LITERATURE REVIEW

In this section, we provide an extensive review of pertinent studies that have investigated the detection of diabetic retinopathy through the utilization of Convolutional Neural Network (CNN) models. The emergence of CNNs has significantly influenced medical image analysis by enabling automated feature learning and extraction from images. This capability renders CNNs highly effective for tasks like diabetic retinopathy detection. Notably, the insights gleaned from these studies have played a pivotal role in informing the methodologies and approaches adopted in our project.

These studies on diabetic retinopathy detection using machine learning techniques provides a comprehensive understanding of the current state-of-the-art methodologies, models, and approaches in the field. The studies reviewed have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) and other deep learning techniques in accurately detecting and classifying diabetic retinopathy from retinal images. These findings underscore the potential of machine learning algorithms to revolutionize the diagnosis and management of diabetic retinopathy, a leading cause of vision loss worldwide.

2.1 Diabetic Retinopathy Detection Using CNN Model

In the realm of diabetic retinopathy detection, a multitude of studies have delved into the effectiveness of Convolutional Neural Network (CNN) models. These investigations, led by authors Kashif Moin, Mayank Shrivastava, Amlan Mishra, Lambodar Jena, and Soumen Nayak, have encompassed a diverse array of CNN architectures, spanning from well-established models like VGG, ResNet, and Inception to bespoke networks tailored for specific applications. Operating on extensive datasets of retinal images meticulously annotated with varying severity levels of diabetic retinopathy, these models undergo rigorous training processes.

The performance of CNN-based diabetic retinopathy detection models exhibits a spectrum of accuracies across different studies, albeit predominantly demonstrating remarkable efficacy. Noteworthy are instances where studies have reported accuracy rates exceeding 90% on validation datasets, underscoring the robustness of CNN models in precisely discerning diabetic retinopathy lesions. Furthermore, the evolution of CNN architectures and training methodologies, as observed by Moin et al., has propelled continual enhancements in model accuracy over successive iterations.

An additional avenue of exploration undertaken by researchers involves the adoption of the transfer learning paradigm. Herein, as elucidated by Shrivastava et al., pre-trained CNN models on expansive image datasets such as ImageNet serve as foundational frameworks, subsequently fine-tuned for the specific task of diabetic retinopathy detection. This approach capitalizes on the wealth of knowledge encoded within pre-existing CNN architectures, thereby facilitating expedited convergence and heightened performance in diabetic retinopathy diagnostic endeavors.

2.2 Deep Learning Approaches for Detecting Diabetic Retinopathy using CNN Models

M. Mukesh Krishnan, S. Thanga Ramya, K. Kirubanathavalli, and S. Lalitha have contributed significantly to this burgeoning field through their study published by IEEE.

Their research delves into the efficacy of Convolutional Neural Network (CNN) models in detecting diabetic retinopathy, leveraging the inherent capabilities of deep learning. By harnessing large datasets of retinal images, meticulously annotated with diabetic retinopathy severity levels, their study elucidates the potential of CNN architectures in automating the diagnostic process.

They explored the use of CNN models, specifically VGG-16 and VGG-19 architectures, for analyzing retinal fundus images and classifying DR severity levels. The study reported promising results, with the developed system achieving high sensitivity, precision, and specificity rates in DR classification. The utilization of CNNs in this study showcases the potential of deep learning techniques in improving the efficiency and accuracy of DR diagnosis.

Additionally, research efforts have focused on enhancing the performance of CNN-based DR detection systems through the optimization of model architectures and training methodologies. For instance, they investigated the efficacy of weighted filters in conjunction with CNNs for DR detection, achieving notable improvements in classification accuracy.

Despite the advancements in CNN-based DR detection, challenges remain, particularly concerning the generalization of models across diverse datasets and the interpretability of model predictions. Future research directions may involve exploring ensemble learning techniques, transfer learning approaches, and domain adaptation strategies to address these challenges and further enhance the robustness of DR detection systems.

2.3 Diabetic Retinopathy Detection and Classification Using LBP and CNN

A study conducted by Vamsi Krishna et al. investigated the effectiveness of integrating LBP features with CNN architectures for DR detection and classification. The utilization of LBP enables the extraction of texture features from retinal images, complementing the deep learning capabilities of CNNs. The study employed a hybrid approach, where LBP features were extracted from retinal images and subsequently fed into a CNN model for classification. The study reported promising results, demonstrating the potential of the LBP-CNN hybrid approach in accurately detecting and classifying DR severity levels. By combining texture-based features with learned representations from CNNs, the proposed method achieved notable improvements in classification performance compared to traditional CNN-based approaches.

Furthermore, the integration of LBP with CNNs offers several advantages, including enhanced robustness to variations in image quality, illumination, and noise. The texture-based features extracted by LBP provide valuable supplementary information to the CNN model, contributing to more discriminative feature representations and improved classification accuracy.

While the LBP-CNN approach shows promise in DR detection and classification, further research is needed to explore its scalability and generalization across diverse datasets. Additionally, the interpretability of the combined model's predictions warrants investigation to ensure clinical relevance and trustworthiness.

2.4 Diabetic Retinopathy Detection using Weighted Filters and Classification using CNN.

An investigation into enhancing diabetic retinopathy (DR) detection and classification led Anas Bilal, Guangmin Sun, and Sarah Mazha to explore the integration of weighted filters with Convolutional Neural Networks (CNNs).

The study focused on enhancing feature extraction from retinal images using weighted filters, which assign different importance weights to image pixels based on their relevance to DR lesions. By incorporating weighted filtering techniques into the preprocessing stage, the study aimed to highlight relevant features associated with DR pathology, thus facilitating more effective classification by the CNN model.

The weighted filter-enhanced images were subsequently fed into a CNN architecture for classification, leveraging the deep learning capabilities of CNNs to learn discriminative features from the pre-processed images. The CNN model was trained on a dataset of annotated retinal images, enabling it to distinguish between different DR severity levels and accurately classify retinal abnormalities indicative of DR.

The results of the study demonstrated promising outcomes, with the weighted filter-enhanced CNN model achieving notable improvements in DR detection and classification performance compared to conventional CNN-based approaches. By integrating weighted filtering techniques into the preprocessing pipeline, the model was able to enhance feature representation and capture subtle pathological changes associated with DR.

Furthermore, the study highlighted the potential of combining traditional image processing methods, such as weighted filtering, with state-of-the-art deep learning techniques to improve the diagnostic capabilities of automated DR detection systems. The synergistic integration of weighted filters and CNNs offers a holistic approach to DR detection, leveraging the strengths of both methodologies to enhance classification accuracy and robustness.

While the proposed approach shows promise in DR detection, further research is needed to validate its performance across diverse datasets and clinical settings. Additionally, the scalability and computational efficiency of the weighted filter-enhanced CNN model warrant investigation to ensure its practical applicability in real-world healthcare scenarios.

2.5 Machine Learning Styles for Diabetic Retinopathy Detection: A Review and Bibliometric Analysis

The study titled "Machine Learning Styles for Diabetic Retinopathy Detection: A Review and Bibliometric Analysis," Shyamala Subramanian, Sashikala Mishra, Shruti Patil, Kailash Shaw, and Ebrahim Aghajari conduct a thorough examination of machine learning methodologies utilized in the detection of diabetic retinopathy. The study dives into various machine learning approaches, including convolutional neural networks (CNNs), support vector machines (SVMs), decision trees, and ensemble methods, among others. By analysing existing literature and employing bibliometric techniques, the authors provide insights into the trends, advancements, and challenges in the field of diabetic retinopathy detection using machine learning.

The review encompasses a wide range of research articles, conference papers, and patents related to diabetic retinopathy detection, highlighting the diversity of approaches employed by researchers. The authors categorize the literature based on the machine learning algorithms utilized, the types of retinal images analysed, and the performance metrics evaluated. Additionally, they identify key research trends, such as the increasing use of deep learning techniques like CNNs and the integration of multi-modal data for improved detection accuracy.

Furthermore, the study includes a bibliometric analysis, which involves quantifying the volume and impact of research publications in the field. By examining citation counts, publication trends, and collaboration networks, the authors provide insights into the dissemination and influence of diabetic retinopathy detection research. This bibliometric analysis offers valuable information for researchers, policymakers, and healthcare professionals interested in understanding the landscape of diabetic retinopathy detection research.

3. DATASET DESCRIPTION AND ANALYSIS

3.1 Dataset Description

Source:

The dataset originates from EyePACS, a prominent platform dedicated to storing and analyzing retinal images for diabetic retinopathy (DR) screening. EyePACS serves as a centralized repository for ophthalmologists and healthcare professionals to securely store and access retinal images obtained during routine screenings for diabetic retinopathy.

EyePACS Platform:

EyePACS is designed to streamline the process of diabetic retinopathy screening by leveraging digital retinal imaging technology. It provides a comprehensive solution for managing and analysing retinal images, facilitating efficient diagnosis and treatment planning for patients with diabetes. The platform offers features such as image storage, image viewing, annotation tools, and diagnostic reporting capabilities, enabling healthcare providers to efficiently assess retinal health and detect signs of diabetic retinopathy.

About Dataset:

The Diabetic Retinopathy Classification Dataset, sourced from EyePACS and available on Kaggle, comprises a diverse collection of retinal images obtained from individuals with varying degrees of diabetic retinopathy. These images capture the pathological changes associated with diabetic retinopathy, including microaneurysms, haemorrhages', exudates, and neovascularization. Each image in the dataset is meticulously evaluated and graded by experienced clinicians, who assign a severity level ranging from 0 to 4 based on the presence and extent of diabetic retinopathy lesions.

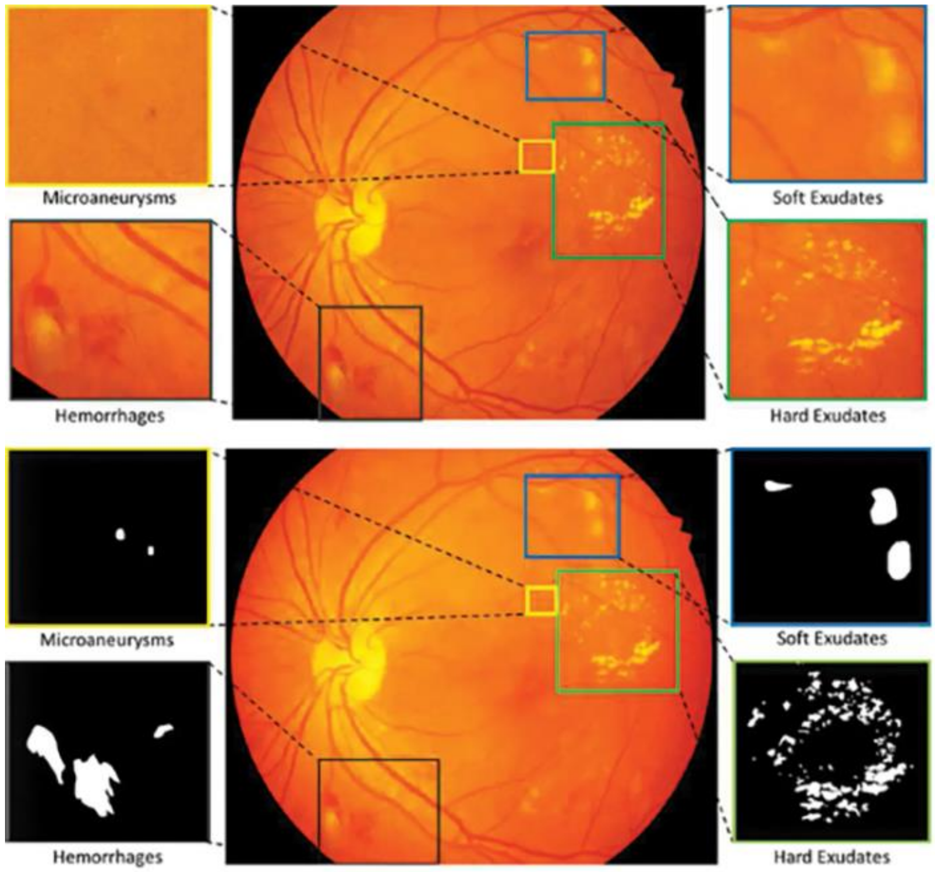

Fig 3.1.1 DR Retinal Features

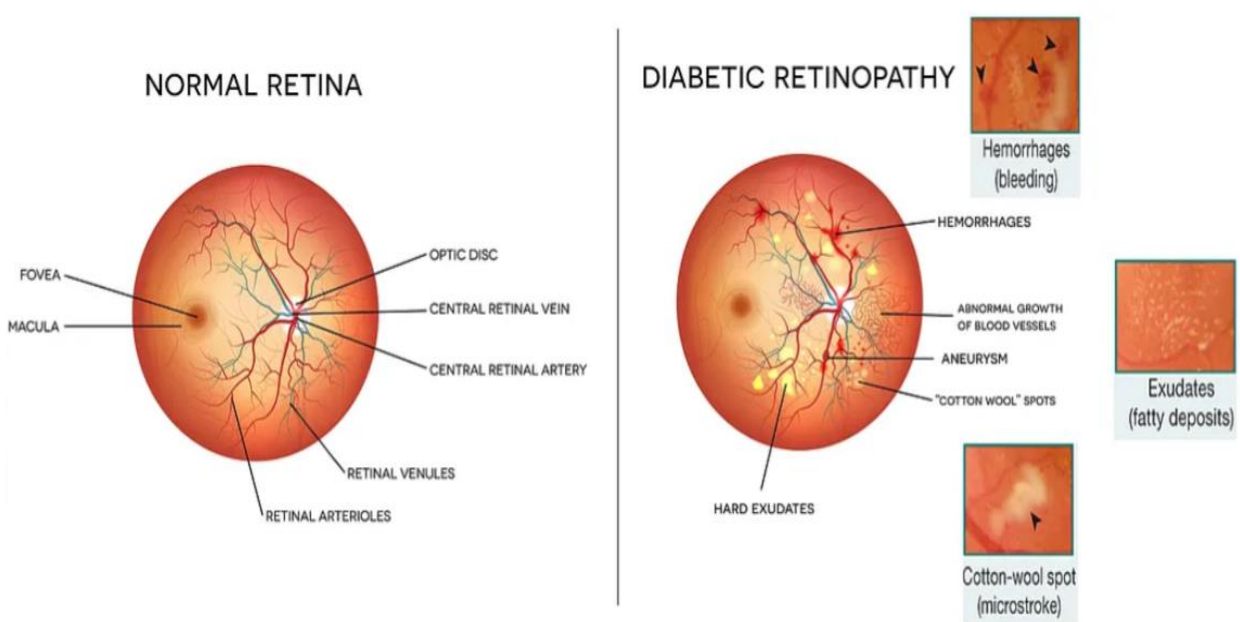

Fig 3.1.2 Difference between normal retina and DR retina

Classes:

1. No DR (Class 0): Images in this category depict retinas without any discernible signs of diabetic retinopathy. This class serves as a reference for normal retinal anatomy and comprises a substantial portion of the dataset.

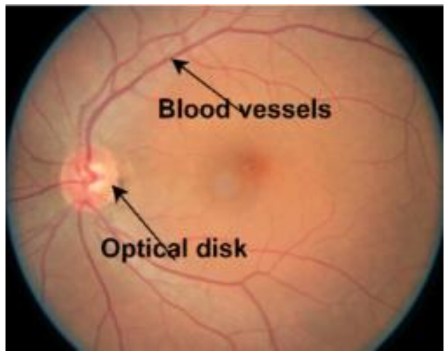

Fig 3.1.3 No DR

2. Mild DR (Class 1): Images in this category exhibit early signs of diabetic retinopathy, such as mild microaneurysms and retinal haemorrhages. These abnormalities are indicative of early-stage retinal damage associated with diabetes.

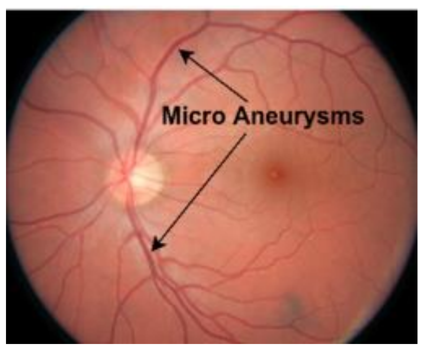

Fig 3.1.4 Mild DR

3.Moderate DR (Class 2): Images in this category display moderate diabetic retinopathy characterized by the presence of more pronounced lesions, including exudates and intraretinal microvascular abnormalities (IRMAs).

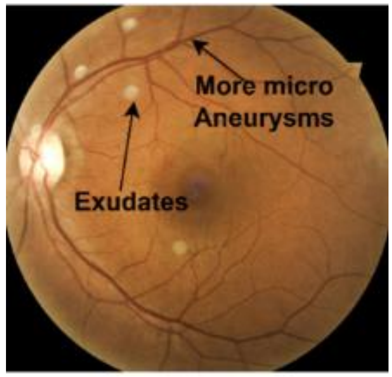

Fig 3.1.5 Moderate DR

4. Severe DR (Class 3): Images in this category indicate advanced stages of diabetic retinopathy, with extensive retinal damage and widespread vascular abnormalities. Severe haemorrhages, cotton-wool spots, and venous beading may be observed in these images.

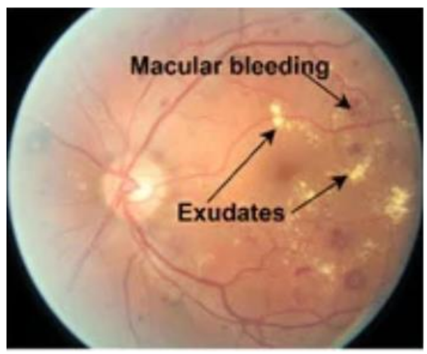

Fig 3.1.6 Severe DR

5. Proliferative DR (Class 4): Images in this category depict proliferative diabetic retinopathy, the most severe form of the condition. These images often feature neovascularization, fibrous proliferation, and vitreous haemorrhage, posing a significant risk of vision loss and retinal detachment.

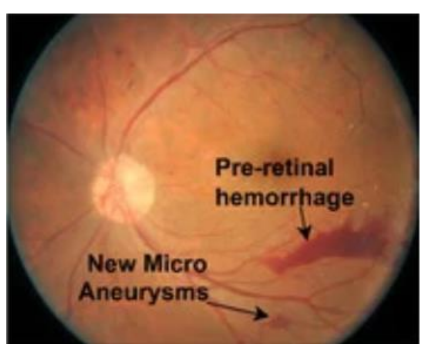

Fig 3.1.7 Proliferative DR

Data Split:

To facilitate model training and evaluation, the dataset has been partitioned into distinct subsets for training and testing purposes. The training set comprises a subset of images used to train machine learning models, while the test set contains a separate set of images reserved for model validation and performance assessment.

Overall, the Diabetic Retinopathy Classification Dataset sourced from EyePACS provides a valuable resource for developing and evaluating machine learning algorithms aimed at automating the detection and classification of diabetic retinopathy from retinal images. By leveraging this dataset, researchers and healthcare professionals can advance the development of accurate and efficient diagnostic tools for diabetic retinopathy screening, ultimately improving patient outcomes and enhancing the management of diabetes-related eye complications.

3.2 Preprocessing

3.2.1 Data augmentation

These techniques are employed to increase the diversity and robustness of the dataset by creating variations of existing images. In the context of retinal images for diabetic retinopathy classification, common augmentation techniques include:

Rotation: Rotating images from a certain angle to simulate variations in orientation.

Horizontal and Vertical Flipping: Flipping images horizontally or vertically to introduce mirror reflections.

Scaling: Resizing images to different scales to simulate variations in image size.

Translation: Shifting images horizontally or vertically to simulate changes in position.

Brightness and Contrast Adjustment: Modifying brightness and contrast levels to simulate changes in lighting conditions.

Noise Injection: Adding random noise to images to simulate imaging artifacts or sensor noise.

Elastic Deformation: Applying elastic transformations to deform images and introduce distortions.

By applying these augmentation techniques, the dataset's size can be effectively increased, and the models can be trained on a more diverse range of image variations. This helps improve the model's generalization ability and robustness to variations in input data, ultimately enhancing its performance on unseen test data.

3.2.2 Visual Inspection of Class Imbalance in the Training Set

In the context of our project focused on diabetic retinopathy detection, assessing class distribution within the training dataset is paramount. This process involves visually examining the distribution of retinal images across different severity levels of diabetic retinopathy. By visually inspecting the distribution, we aim to identify any disparities in sample frequencies across severity levels, which can impact the model's ability to effectively learn from all classes.

We utilized data visualization tools such as Matplotlib to plot the distribution of retinal images across severity levels of diabetic retinopathy. Each severity level corresponds to a class label, ranging from 0 (no diabetic retinopathy) to 4 (proliferative diabetic retinopathy), indicating the severity of the condition. The resulting visualization provides insights into the relative frequencies of retinal images within each severity level, facilitating the detection of class imbalances.

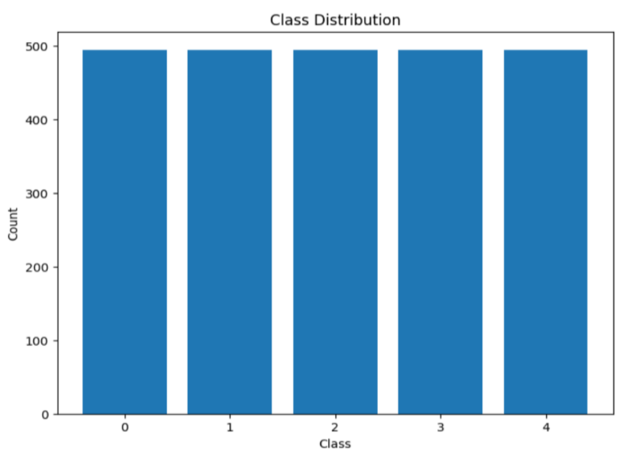

Fig 3.2.2.1 Class Distribution

3.2.3 Visualization of Retinal Images from the Training Dataset

In our project pipeline for diabetic retinopathy detection, the next step after assessing class distribution involved visualizing retinal images from the training dataset. This visualization aimed to provide insights into the characteristics of the retinal images and ensure data quality before feeding them into the deep learning model.

We utilized Matplotlib, a popular data visualization library, to plot a subset of retinal images from the training dataset. Each image was displayed alongside its corresponding class label, representing the severity level of diabetic retinopathy. By visually inspecting these images, we gained a better understanding of the dataset's composition and the visual manifestations of diabetic retinopathy across different severity levels.

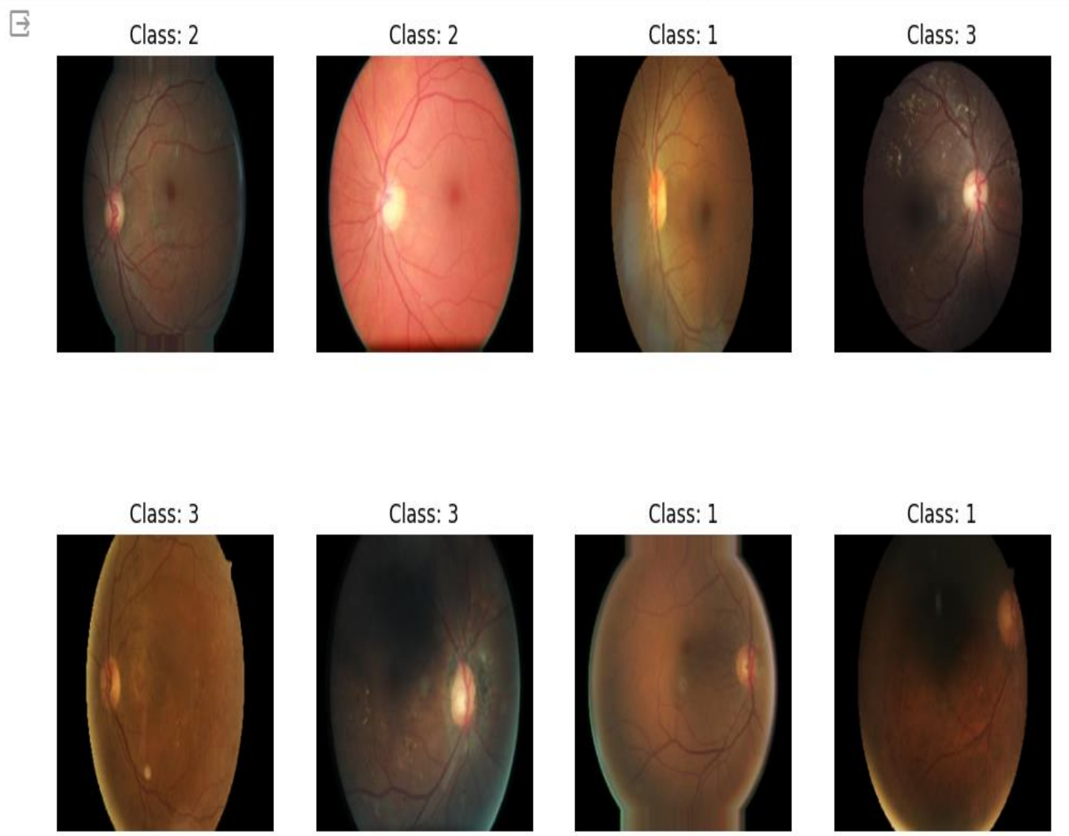

Fig 3.2.3.1 Retinal Class Images

During the image visualization process, we carefully examined the retinal images for any anomalies or artifacts that could affect model performance. This included assessing image clarity, presence of abnormalities, and consistency in labeling. Any inconsistencies or data anomalies identified during this visual inspection were documented for further investigation and potential data cleaning steps.

3.3 Tools Used

The research employed a variety of tools and technologies to facilitate data processing, model development, and user interface (UI) design. The following tools were instrumental in conducting the study:

- Programming Language:

  Python: Python programming language served as the primary language for coding and implementing various algorithms and models due to its versatility and extensive library support.

- Deep Learning Framework:

  TensorFlow: TensorFlow, an open-source deep learning framework developed by Google, was utilized for building and training deep neural network models. Its high-level APIs and computational efficiency were leveraged to develop sophisticated models for diabetic retinopathy detection.

- User Interface Development:

  Streamlit: Streamlit, a Python library for building interactive web applications, was employed to develop the user interface for the research project. Streamlit's intuitive syntax and rapid prototyping capabilities enabled the creation of interactive dashboards and visualization tools for exploring model predictions and results.

  Visual Studio Code: Visual Studio Code, a lightweight and versatile code editor, was utilized for software development tasks, including writing, debugging, and testing code. Its extensive ecosystem of extensions and integrated Git support facilitated seamless development and collaboration workflows.

4. METHODOLOGY

4.1 Model Building

Convolutional Neural Network

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision by enabling automated feature extraction and hierarchical learning from raw image data. These architectures are specifically designed to process visual data efficiently, making them well-suited for tasks like diabetic retinopathy detection, where accurate interpretation of retinal images is crucial for diagnosis and treatment planning. CNNs consist of multiple layers, including convolutional layers, which apply learnable filters to input images to extract features; pooling layers, which down sample feature maps to reduce computational complexity; and fully connected layers, which perform classification based on the learned features. One of the key advantages of CNN architectures is their ability to automatically learn relevant features from raw pixel values, eliminating the need for manual feature engineering. Additionally, CNNs leverage parameter sharing and local receptive fields to capture spatial dependencies in images effectively, enabling them to learn complex patterns and structures inherent in retinal images. Despite their effectiveness, CNN architectures also come with challenges such as computational complexity, the risk of overfitting, and difficulties in interpretability. However, advancements in regularization techniques, architecture design, and training methodologies have mitigated many of these challenges, making CNNs indispensable tools for medical image analysis tasks like diabetic retinopathy detection. With their ability to generalize well to diverse datasets and achieve state-of-the-art performance, CNN architectures continue to drive advancements in the field of healthcare and medical imaging.

4.1.1 Sequential CNN Architecture:

The Sequential CNN architecture is a fundamental and widely used model for image classification tasks, including diabetic retinopathy detection. In a Sequential model, layers are arranged sequentially, with each layer passing its output to the next layer in the sequence. This architecture typically includes convolutional layers, activation functions such as ReLU

(Rectified Linear Unit) to introduce non-linearity, pooling layers for spatial down-sampling, and fully connected layers for classification. The Sequential model's simplicity and ease of implementation make it an attractive choice, particularly for beginners or for tasks where interpretability and computational efficiency are paramount. However, its linear structure may limit its ability to capture complex patterns and relationships in images compared to more sophisticated architectures like ResNet or DenseNet.

In the construction of the Sequential CNN architecture, several key design choices were made to optimize model performance for diabetic retinopathy detection.

- Activation Function and Learning Rate:

  The Rectified Linear Unit (ReLU) activation function was chosen for its ability to introduce non-linearity and accelerate convergence during training. ReLU effectively addresses the vanishing gradient problem, allowing the model to learn complex patterns in the data more efficiently. Additionally, the learning rate for the Adam optimizer was set to 1e-4, a commonly used value that balances the trade-off between convergence speed and stability.

- Batch Normalization and Pooling Layers:

  Batch normalization layers were inserted after each convolutional layer to stabilize and accelerate the training process. By normalizing the activations of each layer, batch normalization reduces internal covariate shift and ensures more stable gradients during backpropagation. Additionally, MaxPooling2D layers with a pool size of (2, 2) were employed after each convolutional block to downsample feature maps and reduce spatial dimensions. This pooling operation helps in capturing the most salient features while reducing computational complexity.

- Dense Layers and Dropout Regularization:

  Following the convolutional layers, Dense fully connected layers were introduced to perform classification based on the extracted features. Two Dense layers with 512 and 256 units, respectively, were included to progressively distil the learned representations into class predictions. To prevent overfitting and improve model generalization, Dropout regularization with a rate of 0.5 was applied after each Dense layer. Dropout randomly deactivates a fraction of neurons during training, forcing the model to learn more robust and invariant features.

- Model Compilation and Training Configuration:
  The model was compiled using the Adam optimizer with a learning rate of 1e-4 and categorical cross-entropy loss function, suitable for multi-class classification tasks. During training, the model's performance was evaluated using accuracy as the primary metric, measuring the proportion of correctly classified samples.

Sequential CNNs may struggled to achieve optimal performance on datasets with intricate features or large variations in image characteristics.

Despite these limitations, the Sequential CNN architecture serves as a foundational model for understanding CNNs and can provide competitive performance when appropriately tuned and trained for diabetic retinopathy detection tasks.

4.1.2 ResNet50

The ResNet50 architecture stands out as a profound advancement in convolutional neural networks (CNNs), particularly notable for its depth and efficacy in image classification tasks. Developed by Microsoft Research, ResNet50 introduces the concept of residual learning, addressing the challenge of vanishing gradients encountered in training very deep networks. By incorporating residual blocks with skip connections, ResNet50 enables the training of exceptionally deep models while mitigating degradation issues, thus enhancing performance on complex visual recognition tasks. In the context of diabetic retinopathy detection, ResNet50's deep and hierarchical architecture proves advantageous for extracting relevant features from retinal images. Its ability to capture intricate patterns and subtle details is instrumental in identifying pathological changes associated with different stages of diabetic retinopathy. Moreover, ResNet50's transfer learning potential is leveraged by fine-tuning pre-trained models on specific tasks, facilitating efficient utilization of available data and faster convergence during training.

The GlobalAveragePooling2D layer, as employed in the ResNet50 architecture, facilitates effective global representation learning by aggregating spatial information across feature maps. This pooling operation aids in summarizing the spatial information contained in the feature maps, leading to a condensed representation of the image features. By averaging the values in each feature map, GlobalAveragePooling2D reduces the spatial dimensions while retaining essential information relevant to the classification task. In the context of diabetic retinopathy detection, this pooling layer plays a crucial role in extracting discriminative features from retinal images, contributing to the overall performance of the model.

4.1.3 DenseNet121

DenseNet121 is a convolutional neural network architecture that has gained popularity for its dense connectivity pattern and efficient feature reuse mechanism. Unlike traditional convolutional neural networks where each layer is connected only to the subsequent layer, DenseNet introduces skip connections that connect every layer to every other layer in a feed-forward fashion. This dense connectivity promotes feature reuse and facilitates gradient flow throughout the network, mitigating the vanishing gradient problem commonly encountered in deep networks.

One of the key advantages of DenseNet121 is its ability to capture intricate features at different levels of abstraction, leading to more discriminative representations of the input data. By concatenating feature maps from previous layers, DenseNet enables each layer to directly access the gradients from all subsequent layers, enhancing information flow and enabling the network to learn more complex representations.

Moreover, DenseNet architectures are known for their parameter efficiency and robustness to overfitting, owing to their dense connectivity and feature reuse mechanism. This allows DenseNet121 to achieve competitive performance even with fewer parameters compared to other architectures.

In the context of diabetic retinopathy detection, DenseNet121's dense connectivity and efficient feature reuse make it particularly well-suited for capturing subtle patterns and abnormalities in retinal images. By leveraging its dense connections, the model can effectively learn and exploit the intricate relationships between features, leading to improved classification accuracy.

The DenseNet121 model was employed in the research project to harness its robust capabilities in image classification tasks, diabetic retinopathy detection. This model, pre-trained on the ImageNet dataset, offers a deep architecture that facilitates effective feature extraction from input images. The utilization of the DenseNet121 architecture enables the automatic learning of hierarchical features, leveraging dense connections between layers to enhance information flow and feature reuse.

In the implementation, the Rectified Linear Unit (ReLU) activation function was utilized to introduce non-linearity and enhance the model's capacity to capture complex patterns in the data. Additionally, the learning rate for the Adam optimizer was set to 0.0005, enabling efficient convergence during the training process while preventing overshooting of the optimal solution.

To enhance model generalization and prevent overfitting, a dropout regularization technique was applied with a dropout rate of 0.5 after the fully connected layers. This regularization method aids in reducing model complexity and improves its ability to generalize to unseen data. Furthermore, the categorical cross-entropy loss function was employed to quantify the dissimilarity between predicted and true class distributions, optimizing model performance during training.

Overall, the DenseNet121 model, with its dense connectivity and efficient feature extraction capabilities, proved to be instrumental in achieving high accuracy of 90% in diabetic retinopathy classification tasks. Its ability to automatically learn discriminative features from retinal images, coupled with appropriate hyperparameter settings and regularization techniques, contributed significantly to the success of the research project.

```
[ ]  # Evaluate the model on test data
     test_accuracy = model.evaluate(test_generator)
     print( test_accuracy)

     0.9066666960716248
```

Fig 4.1.3.1 Test Accuracy

4.2 Deployment of the Model

Deploying a machine learning model is a crucial step in transitioning from research to real-world applications. By deploying our DenseNet121 model, we aim to provide a practical solution for diabetic retinopathy detection, making it accessible to healthcare professionals and patients alike. The deployment process enables seamless integration of the model into existing workflows, facilitating timely diagnosis and treatment decisions.

Streamlit serves as a powerful tool for deploying machine learning models with ease and efficiency. As an open-source app framework tailored for Python, Streamlit offers a user-friendly interface that simplifies the development and deployment of interactive data science applications. With Streamlit, developers can create intuitive web-based applications using simple Python scripts, eliminating the need for complex front-end development. Its seamless integration with popular machine learning libraries such as TensorFlow enables rapid prototyping and deployment of ML models.

In the context of our project on diabetic retinopathy detection, Streamlit plays a pivotal role in democratizing access to advanced healthcare technology. By leveraging Streamlit's capabilities, we transform our DenseNet121 model into a user-friendly web application that allows healthcare professionals to upload retinal images and obtain real-time predictions for diabetic retinopathy severity. Streamlit's intuitive interface enables clinicians to interact with the model effortlessly, facilitating quick and accurate diagnosis in clinical settings. Additionally, Streamlit's flexibility allows for seamless integration of future updates and enhancements, ensuring the continuous improvement of our diagnostic tool.

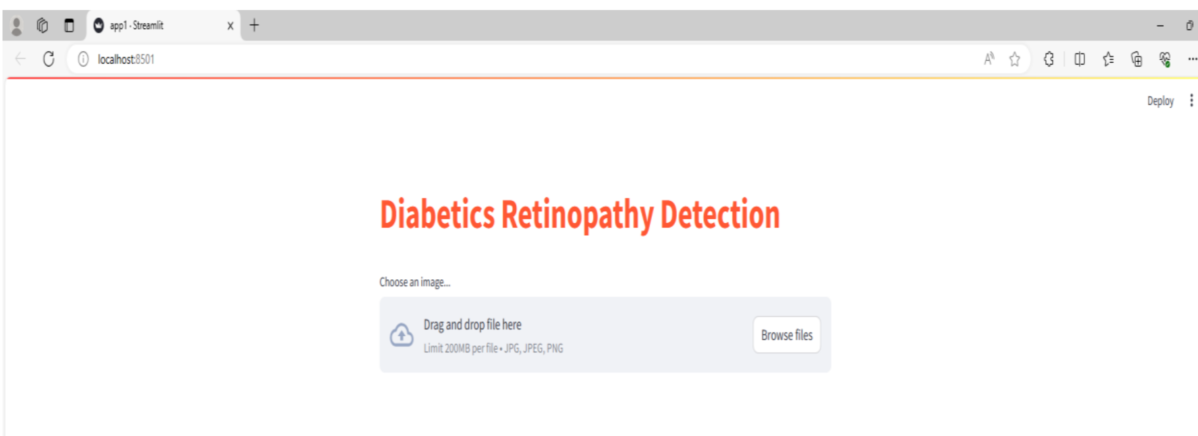

Fig 4.2.1 Streamlit Interface

Overview of the process:

- User Interaction: The UI built with Streamlit provides an intuitive interface where users, typically healthcare professionals, or patients, can interact with the application. They are prompted to upload retinal images directly from their device.

- Image Upload: Upon selecting the option to upload images, users can browse their local files and select the retinal images they wish to analyse. The selected images are then uploaded to the application.

- Model Prediction: Once the images are uploaded, the DenseNet121 model deployed in the backend processes these images. The model leverages its deep learning architecture to analyse the features present in the retinal images and make predictions regarding the severity level of diabetic retinopathy.

- Prediction Display: The predictions generated by the model are displayed on the UI in real-time. Users can view the predicted severity level associated with each uploaded retinal image.

- Interpretation and Action: Based on the predictions provided by the model, users, particularly healthcare professionals, can interpret the severity level of diabetic retinopathy in the retinal images. This information can guide them in making informed decisions regarding patient care, such as scheduling follow-up appointments, initiating treatment, or referring patients to specialists for further evaluation.

5. RESULT AND DISCUSSIONS

The developed user interface (UI) for diabetic retinopathy detection represents a significant advancement in ophthalmic care, offering a sophisticated platform for early detection, assessment, and management of diabetic retinopathy. By seamlessly integrating technology into clinical practice, the UI has the potential to revolutionize diabetic retinopathy screening and contribute to improved patient outcomes and vision health.

Real-time Prediction: The user interface for diabetic retinopathy detection harnesses the power of state-of-the-art machine learning algorithms to provide rapid and accurate predictions of diabetic retinopathy severity levels. Upon image upload, the interface initiates real-time processing of the retinal image data, leveraging sophisticated convolutional neural networks (CNNs) to extract intricate features indicative of diabetic retinopathy pathology. These CNNs, trained on vast datasets of annotated retinal images, have learned to discern subtle patterns and abnormalities associated with varying degrees of diabetic retinopathy, enabling precise classification of disease severity.

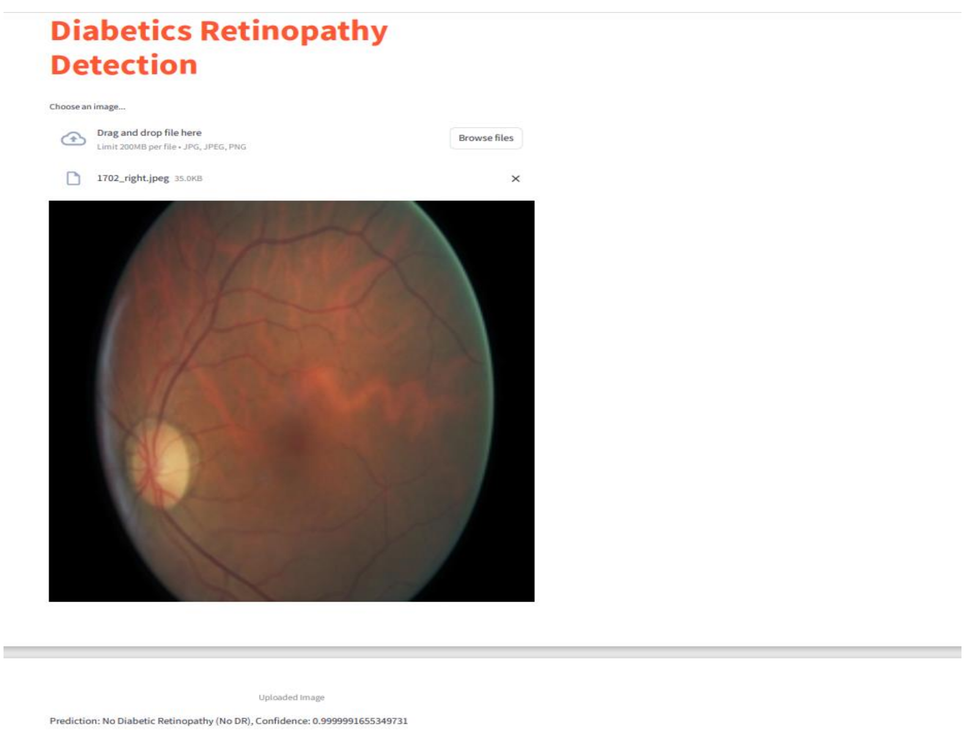

Fig 5.1 UI Prediction -No DR

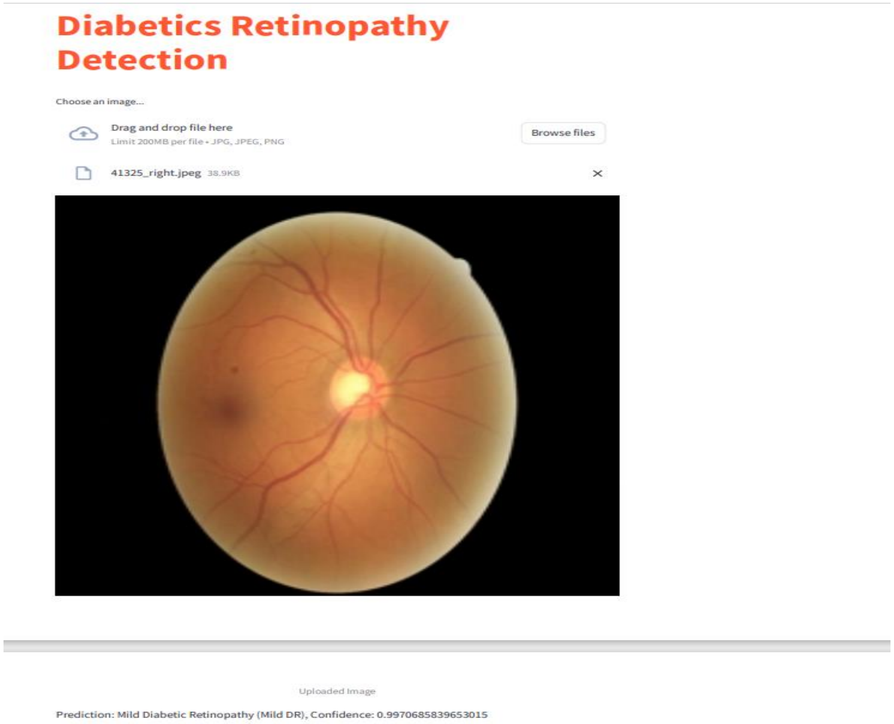

Fig 5.2 UI Prediction -Mild DR

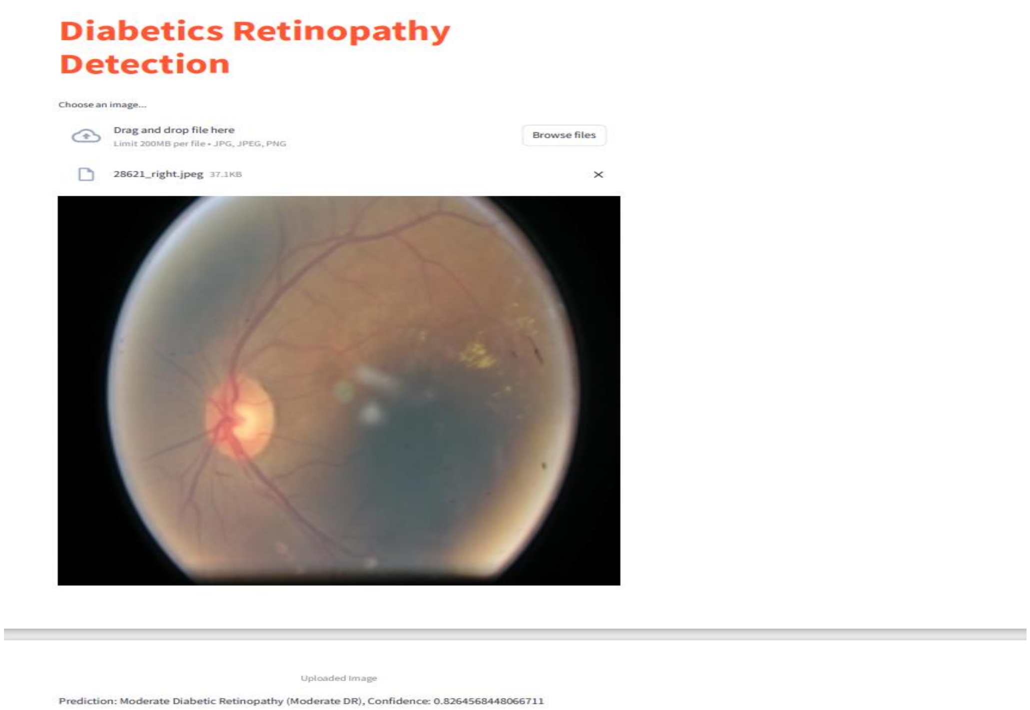

Fig 5.3 UI Prediction -Moderate DR

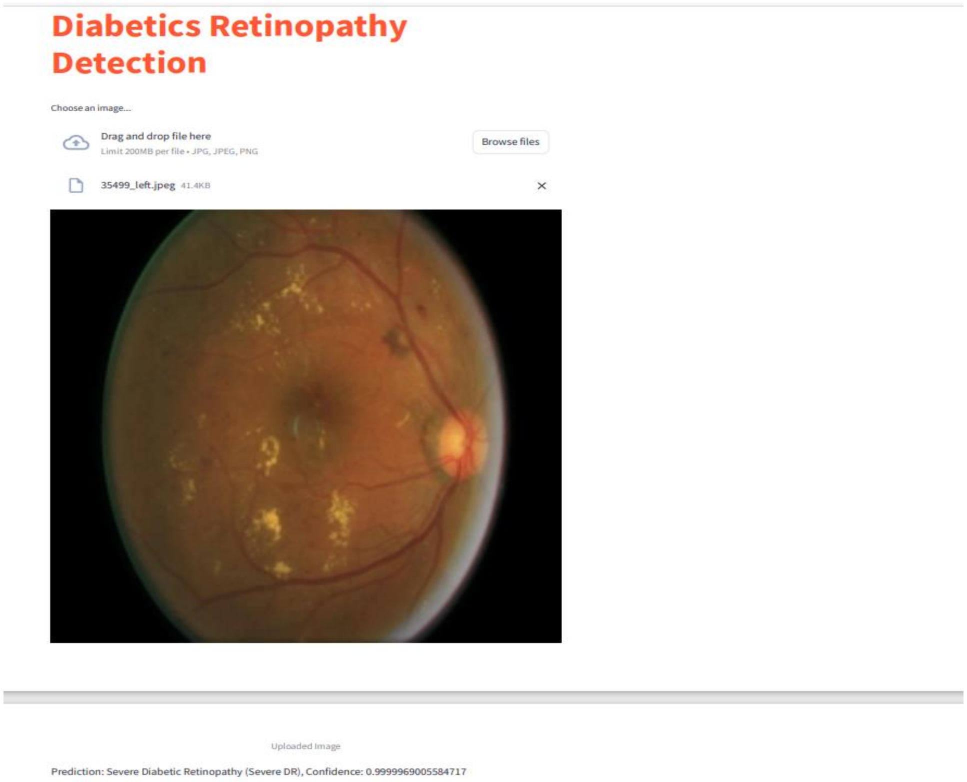

Fig 5.4 UI Prediction -Severe DR

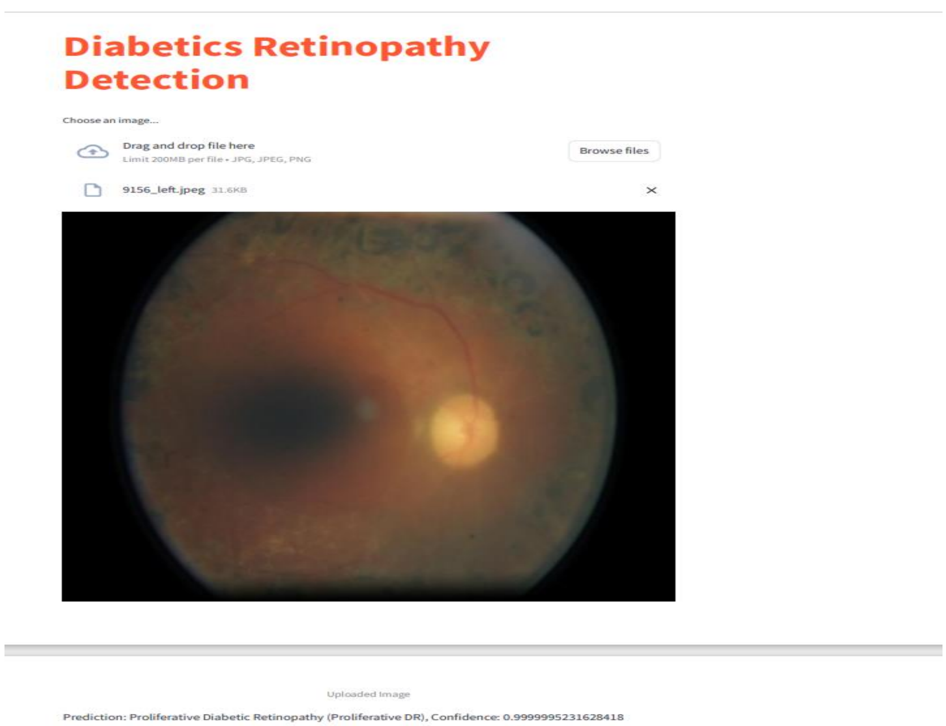

Fig 5.5 UI Prediction -Proliferative DR

Clinical Implications: The implementation of the UI carries significant implications for clinical practice, particularly in the early detection and management of diabetic retinopathy. By providing healthcare professionals with efficient tools for retinal image analysis, the UI streamlines diagnostic workflows and enhances diagnostic accuracy. Clinicians can leverage the predictive capabilities of the UI to triage patients, prioritize interventions, and monitor disease progression over time. Moreover, the UI facilitates seamless communication and collaboration among multidisciplinary care teams, enabling timely consultations and treatment planning.

Patient Engagement: Beyond its utility for healthcare professionals, the UI serves as a valuable resource for patient engagement and education. Patients can actively participate in their eye health management by uploading retinal images through the user-friendly interface and receiving personalized feedback on detected diabetic retinopathy severity levels. This interactive approach empowers patients to take an active role in their care, fostering greater adherence to treatment plans and promoting long-term vision health. Additionally, the UI facilitates remote consultations and telemedicine appointments, providing patients with convenient access to specialized care regardless of geographical location.

5.1 Limitations

1. Image Quality Dependency: The performance of the user interface for diabetic retinopathy detection is contingent upon the quality of retinal images uploaded by users. Poor image quality, such as low resolution or inadequate focus, may hinder the accuracy of predictions and lead to misinterpretation of results. Addressing this limitation requires educating users on optimal imaging techniques and implementing preprocessing algorithms to enhance image clarity and consistency.

2. Interpretability Challenges: While the user interface delivers real-time predictions of diabetic retinopathy severity levels, the interpretability of these predictions may pose challenges for users, particularly those without specialized ophthalmic training. Complex machine learning models, such as convolutional neural networks (CNNs), inherently lack transparency in their decision-making processes, making it difficult for users to understand the rationale behind predictions. Enhancing interpretability through model visualization techniques and explanatory features could mitigate this limitation.

3. Generalization to Diverse Populations: The user interface's performance may vary across different demographic groups and ethnicities, as the underlying machine learning algorithms are trained on datasets that may not fully represent the diversity of retinal pathology observed in clinical practice. Ensuring the generalizability of the interface requires ongoing validation and refinement using diverse and inclusive datasets, encompassing a wide range of patient demographics and disease presentations.

4. Regulatory Compliance and Ethical Considerations: Deploying the user interface in clinical settings necessitates compliance with regulatory standards, such as data privacy regulations (e.g., GDPR, HIPAA) and medical device regulations (e.g., FDA approval). Additionally, ethical considerations surrounding patient consent, data security, and algorithmic bias must be carefully addressed to safeguard patient rights and mitigate potential risks associated with technology-enabled healthcare interventions.

5. Integration with Clinical Workflow: Successful implementation of the user interface hinges on its seamless integration into existing clinical workflows and electronic health record (EHR) systems. Challenges may arise in interoperability, data exchange protocols, and user adoption, requiring close collaboration between developers, healthcare providers, and IT professionals to ensure smooth integration and user acceptance.

6. Limited Scope of Application: While the user interface excels in diabetic retinopathy detection, its utility may be limited to a specific clinical domain. Expanding the interface's functionality to encompass other ocular diseases or broader healthcare applications would necessitate additional development efforts and validation studies to ensure accuracy and reliability across diverse diagnostic tasks.

5.2 Future Directions

1. Enhanced Model Interpretability: Invest in research and development efforts to improve the interpretability of the machine learning models underlying the diabetic retinopathy detection interface. Exploring techniques such as attention mechanisms, saliency maps, and model-agnostic interpretability methods can provide insights into the features driving predictions, enabling users to better understand and trust the diagnostic outputs.

2. Integration of Multimodal Data: Expand the capabilities of the user interface by integrating multimodal data sources, such as optical coherence tomography (OCT) scans, visual field

tests, and patient demographics. By leveraging complementary information from diverse imaging modalities and clinical parameters, the interface can enhance diagnostic accuracy, facilitate personalized risk stratification, and support comprehensive management strategies for diabetic retinopathy.

3. Continuous Model Improvement: Establish mechanisms for continuous model improvement and validation using real-world clinical data and feedback from users. Implementing robust quality assurance processes, monitoring model performance metrics, and conducting periodic retraining cycles can ensure that the diabetic retinopathy detection interface remains up-to-date, accurate, and clinically relevant over time.

4. Deployment in Teleophthalmology Settings: Explore opportunities to deploy the user interface in teleophthalmology settings to extend access to diabetic retinopathy screening and management in underserved or remote areas. By enabling remote image capture, interpretation, and consultation, the interface can bridge gaps in healthcare delivery, particularly in regions with limited access to specialized eye care services.

5. Patient-Centered Education and Engagement: Integrate patient-centered educational resources and engagement features into the user interface to empower individuals with diabetes to actively participate in their eye health management. Providing personalized risk assessments, preventive recommendations, and educational materials tailored to patients' needs and preferences can promote early detection, adherence to treatment, and long-term vision preservation.

6. Collaboration and Knowledge Sharing: Foster collaborative partnerships between interdisciplinary stakeholders, including clinicians, researchers, technologists, and patient advocacy groups, to drive innovation and knowledge sharing in diabetic retinopathy detection and management. By leveraging collective expertise, resources, and networks, the interface can evolve as a dynamic tool that addresses emerging challenges and advances in the field of ophthalmology and diabetes care.

6.CONCLUSION

The development and implementation of the diabetic retinopathy detection interface marks a significant milestone in the intersection of healthcare and technology, with profound implications for ophthalmic care and patient outcomes. Through the seamless integration of deep learning algorithms, user-centric design principles, and real-time functionality, the interface empowers healthcare professionals to conduct rapid, accurate, and accessible screening for diabetic retinopathy, a leading cause of vision loss worldwide.

By harnessing the power of artificial intelligence and machine learning, the interface enhances the efficiency, accuracy, and scalability of diabetic retinopathy screening, facilitating early detection and timely intervention to prevent vision-threatening complications. Furthermore, the interface serves as a catalyst for innovation in teleophthalmology, enabling remote access to specialized eye care services and extending the reach of diabetic retinopathy screening to underserved communities and regions with limited healthcare infrastructure.

Moreover, the diabetic retinopathy detection interface embodies the principles of patient-centered care, prioritizing usability, accessibility, and engagement to empower individuals with diabetes to take an active role in their eye health management. By providing real-time predictions, personalized risk assessments, and educational resources, the interface fosters informed decision-making, promotes treatment adherence, and enhances patient outcomes through early detection and intervention.

Looking ahead, the diabetic retinopathy detection interface represents a steppingstone towards a future where technology-driven solutions converge with clinical expertise to revolutionize eye health care. Continued research, innovation, and collaboration are essential to further refine and optimize the interface, ensuring its continued relevance, effectiveness, and impact in addressing the evolving challenges and needs of individuals affected by diabetes and diabetic retinopathy.

7. REFERENCES

1. Das, Dolly & Biswas, Saroj & Bandyopadhyay, Sivaji. (2022). Detection of Diabetic Retinopathy using Convolutional Neural Networks for Feature Extraction and Classification (DRFEC). Multimedia Tools and Applications. 82. 1-59. 10.1007/s11042-022-14165-4.
2. Moin, K., Shrivastava, M., Mishra, A., Jena, L., & Nayak, S. (2022). Diabetic Retinopathy Detection Using CNN Model. In Ambient Intelligence in Health Care (pp. Page numbers). Springer Nature Singapore.
3. S. Dua, N. Kandiraju and H. W. Thompson, "Design and implementation of a unique blood-vessel detection algorithm towards early diagnosis of diabetic retinopathy", International Conference on Information Technology: Coding and Computing (ITCC'05), vol. II, no. 1, pp. 26-31, 2005.
4. H. Jiang, K. Yang, M. Gao, D. Zhang, H. Ma and W. Qian, "An Interpretable Ensemble Deep Learning Model for Diabetic Retinopathy Disease Classification", 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2045-2048, 2019.
5. Mukesh Krishnan, M., Thanga Ramya, S., Kirubanathavalli, K., Lalitha, S., Diofrin, J., & Vadivel, M. (2021). Deep Learning Approaches for Detecting Diabetic Retinopathy using CNN Models. IEEE.
6. Raj, Md & Mamun, Md. Al & Faruk, Md. (2020). CNN Based Diabetic Retinopathy Status Prediction Using Fundus Images. 190-193. 10.1109/TENSYMP50017.2020.9230974.
7. Krishna, N. V., Kotilingam, K., Premchand, K., Iqbal, Md. J., & Sudharshana, K. V. S. (2022). Diabetic Retinopathy Detection and Classification Using LBP and CNN. In Proceedings of the 3rd International Conference for Emerging Technology (INCET).
8. Bilal, Anas & Mazhar, Sarah. (2021). Diabetic Retinopathy detection using Weighted Filters and Classification using CNN. 10.1109/CONIT51480.2021.9498466.
9. Subramanian, S., Mishra, S., Patil, S., Shaw, K., & Aghajari, E. (2022). Machine Learning Styles for Diabetic Retinopathy Detection: A Review and Bibliometric Analysis.

10. Al-Omaisi, A., Zhu, C.-Z., Althubiti, S. A., Al-Alimi, D., Xiao, Y.-L., Ouyang, P.-B., & Al-Qaness, M. A. A. (2022). Detection of Diabetic Retinopathy in Retinal Fundus Images Using CNN Classification Models.
11. M. Gandhi and R. Dhanasekaran, "Diagnosis of diabetic retinopathy using morphological process and SVM classifier", 2013 International Conference on Communication and Signal Processing, pp. 873-877, 2013.
12. D. K. Prasad, L. Vibha and K. R. Venugopal, "Early detection of diabetic retinopathy from digital retinal fundus images", 2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS), pp. 240-245, 2015.
13. M. T. Vyshnav, V. Sowmya, E. A. Gopalakrishnan, S. Variyar V.V, V. K. Menon and K. Soman, "Deep Learning Based Approach for Multiple Myeloma Detection", 2020 11th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-7, 2020.
14. M. Shelar, S. Gaitonde, A. Senthilkumar, M. Mundra and A. Sarang, "Detection of Diabetic Retinopathy and its Classification from the Fundus Images", 2021 International Conference on Computer Communication and Informatics (ICCCI), pp. 1-6, 2021.
15. A. P. Bhatkar and G. U. Kharat, "Detection of Diabetic Retinopathy in Retinal Images Using MLP Classifier", 2015 IEEE International Symposium on Nanoelectronic and Information Systems, pp. 331-335, 2015.