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DIABETIC RETINOPATHY DECTECTION USING DEEP LEARNING WITH CNN ALGORITHM AND TRANSFER LEARNING

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Abstract: Diabetic retinopathy (DR) is one of the leading causes of vision loss globally, particularly among individuals with prolonged diabetes. Early detection and timely intervention are critical to preventing severe vision impairment or blindness caused by this condition. However, traditional diagnostic methods rely heavily on manual examination of retinal fundus images by trained ophthalmologists, which is both time-consuming and resource-intensive. In many underserved or rural areas, access to skilled professionals and diagnostic tools is limited, resulting in delayed or missed diagnoses. The need for an automated, scalable, and accurate system for detecting DR stages is paramount. Such a system can significantly reduce the diagnostic burden on healthcare professionals while ensuring timely identification of at-risk patients. The DenseNet169 model, is fine-tuned for DR detection by adding custom classification layers, including a global average pooling layer, dropout for regularization, and a sigmoid-activated dense layer for multilabel classification. This architecture allows the model to capture intricate patterns in retinal images, crucial for detecting subtle variations in DR severity. By leveraging deep learning technologies like DenseNet169 and integrating them into user-friendly platforms like Flask applications, it becomes possible to democratize access to DR screening, improve diagnostic accuracy, and support healthcare providers in managing the growing burden of diabetes-related eye diseases. This study addresses these challenges by proposing a robust and accessible system for DR detection, bridging the gap between advanced technology and practical healthcare solutions.

Keywords: Diabetic Retinopathy (DR) , Deep Learning , DenseNet169 , Retinal Fundus Images, Automated Diagnosis

I. INTRODUCTION

1.1 OVERVIEW

Diabetes or diabetes mellitus is a metabolic disease in which the person body produces an inadequate amount of insulin to produce high blood sugar. In India itself, more than 62 million people are suffering from diabetes. The people who are suffering from diabetes for more than 20 years has 80% chance of causing diabetic retinopathy

According to the International Diabetes Federation, the number of adults with the diabetes in the world is estimated to be 366 million in 2011 and by 2030 this would have risen to 552 million. The number of people with type 2 diabetes is increasing in every country 80% of people with diabetes live in low-and middle-income countries. India stands first with 195% (18 million in 1995 to 54 million in 2025). Previously, diabetes mellitus (DM) was considered to be present, largely, among the urban population in India. Recent studies clearly show an increasing prevalence in rural areas as well. Indian studies show a 3-fold increase in the presence of diabetes among the rural population over the last decade or so (2.2% in 1989 to 6.3% in 2003)

In India, Study shows the estimated prevalence of type 2 diabetes mellitus and diabetic retinopathy in a rural population of south India are nearly 1 of 10 individuals in rural south India, above the age of 40 years.

Diabetic retinopathy is a state of eye infirmity in which damage arises due to diabetes mellitus. It is one of the prominent reason behind blindness. The increased blood sugar due to diabetes incorporated damage to the tiny blood vessels in the retina thereby causing diabetic retinopathy At least 90% of new cases could be reduced with proper medication as well as frequent monitoring of the eyes It primarily affects the retinas of both the eyes, which can lead to vision loss if it is not treated. Poorly controlled blood sugars, high blood pressure, and high cholesterol increase the risk of developing Diabetic retinopathy. The earlier work in the detection of varies stages DR based on explicit feature

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extraction & classification by using various Image Processing techniques & Machine learning algorithm respectively. Though high accuracy can be achieved using these methods but diagnosing diabetic retinopathy based on the explicit extraction of features is an intricate procedure. Due to development of Computer vision in recent times & availability of large dataset, it is now possible to use a deep Neural network for the detection & classification of Diabetic retinopathy.
Hence, several methods have been proposed based on the deep neural network for the classification of Diabetic retinopathy based on severity A major difficulty of fundus image classification using the deep neural network is high variability, especially in the case of retinal proliferation and retinal detachment of new blood vessels, which lowers the accuracy of the network. The method proposed in this paper aims at detecting the various stages of Diabetic Retinopathy by using U-Net segmentation with region merging & Convolutional Neural Network. The retinal segmentation is the process of automatic detection of boundaries of blood vessels within the retina. This allows classifier to learn important features such as retinal proliferation and retinal detachment. The data lost during retinal segmentation is retracted through region merging.

The CNN was initially pre-trained on 10,290 images until it reached a significant level. This was needed to achieve a relatively quick classification result without wasting substantial training time. After 120 epochs of training on the initial images the network was then trained on the full 78,000 training images for a further 20 epochs. Neural networks suffer from severe over-fitting especially in a dataset such as ours in which the majority of the images in the dataset are classified in one class, that showing no signs of retinopathy. To solve this issue, we implemented real-time class weights in the network. For every batch loaded for back-propagation the class-weights were updated with a ratio respective to how many images in the training batch were classified as having no signs of DR. This reduced the risk of over-fitting to a certain class to be greatly reduced.

BACKGROUND

1) Feature Extraction and Representation :
The representation of an image as a 3D matrix having dimension as of height and width of the image and the value of each pixel as depth (1in case of Grayscale and 3 in case of RGB). Further, these pixel values are used for extracting useful features using CNN.

2) Artificial Neural Networks :
Artificial Neural Network is a connections of neurons, replicating the structure of human brain. Each connection of neuron transfers information to another neuron. Inputs are fed into first layer of neurons which processes it and transfers to another layer of neurons called as hidden layers. After processing of information through multiple layers of hidden layers, information is passed to final output layer.

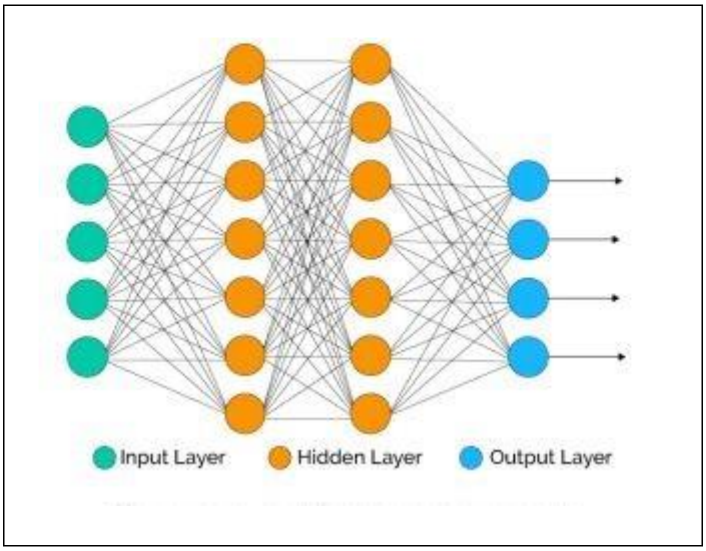

Fig:1.1 ANN

There are capable of learning and they have to be trained. There are different learning strategies:

1. Unsupervised Learning
2. Supervised Learning
3. Reinforcement Learning

3) Convolution Neural Network :

Unlike regular Neural Networks, in the layers of CNN, the neurons are arranged in 3 dimensions: width, height, depth. The neurons in a layer will only be connected to a small region of the layer (window size) before it, instead of all of the neurons in a fully-connected manner. Moreover, the final output layer would have dimensions (number of classes), because by the end of the CNN architecture we will reduce the full image into a single vector of class scores.

4) TensorFlow :

TensorFlow is an open sources of library for numerical computation. First we define the nodes of the computation graph, then inside a session, the Actual computation takes place. TensorFlow is widely used in Machine Learning.

5) Keras :

Keras is a high-level neural networks library written in python that works as a wrapper to TensorFlow. It is used in cases where we want to quickly build and test the neural network with minimal lines of code. It contains implementations of commonly used neural network elements like layers, objective, activation functions, optimizers, and tools to make working with images and text data easier.

6) OpenCV :

OpenCV (OpenSourceComputerVision)isanopensourcelibraryofprogramming functions used for real-time computer-vision. It is mainly used for image processing, video capture and analysis for features like face and object recognition.

II. RELATED WORK

The literature review for the project focused on understanding existing research, academic papers, and relevant articles related to concurrent data access, locking mechanisms, and techniques to ensure data consistency in a shared database environment.

2.1 Dual-Model Approach for Diabetic Retinopathy and Macular Edema Detection, [A. A. Micheal and L. J. Sai]

Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME) are major causes of vision loss in diabetic patients. Early detection is crucial for preventing permanent vision impairment. This research paper proposes a novel dual-model architecture for detecting Diabetic Retinopathy and Diabetic Macular Edema. The proposed framework integrates preprocessing techniques such as circular cropping and Ben’s preprocessing, followed by data augmentation. The Diabetic Retinopathy model is trained on the APTOS2019 dataset, while the Diabetic Macular Edema model is trained using the IDRid dataset. InceptionV3 outperforms other models with an accuracy of 88% for Diabetic Retinopathy classification, while MobileNetV2 outperforms other models with an accuracy of 83% for DME classification. The dual-model architecture enables simultaneous evaluation of retinal images for DR and DME diseases. The Experimental results demonstrate promising outcomes, suggesting the potential effectiveness of the proposed dual-model architecture in diagnosing diabetic eye diseases.

2.2 Deep CNNs for Diabetic Retinopathy Classification: A Transfer Learning Perspective [R. Baskar, E. Sabu and C. Mazo]

Diabetics Retinopathy is a very common eye disease among diabetic patients that affects the blood vessels in the retina, around 3.9 million people are estimated to be affected by diabetic retinopathy globally. Early detection and accurate diagnosis are crucial for timely intervention and management of the disease. On the other hand, in the past few years, deep learning has shown great success in the medical field, and transfer learning is one of the most potent techniques among them. To detect and classify the five diabetic retinopathy stages —normal, mild, moderate, severe, and Proliferative Diabetic Retinopathy (PDR)—, we have trained Alexnet and DenseNet-169 architectures using the APTOS2019 and the Diabetic Retinopathy Competition datasets. Both architectures were tuned on 20,163 images (9000 normal, 2808 mild, 6287 moderate, 1065 severe, and 1003 PDR images) and tested on 2017 images (900 normal, 281 mild, 629 moderate, 107 severe, and 100 PDR images). Among the two architectures, DenseNet-169 showed an overall better result in classifying each stage of diabetic retinopathy. DenseNet169 obtained an F1-score of 0.55, 0.38, 0.40, 0.60, and 0.69 for normal, mild, moderate, severe, and PDR, respectively. This study highlights the potential of transfer learning in improving diabetic retinopathy classification, contributing to early diagnosis and effective management of the disease, and ultimately enhancing patient care and outcomes.

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2.3 Detection and Classification of Diabetic Retinopathy Using Pretrained Deep Neural Networks [A. M. A and S. S. S. Priya]

The retina is harmed by diabetic retinopathy (DR), a consequence of diabetes. Up to, 80% of people who have had diabetes for ten or more years are affected by this type of medical issue. Where the need for diabetic retinopathy identification is greatest, there is frequently a shortage of the necessary knowledge and tools. The majority of research in the area of diabetic retinopathy has relied on manual feature extraction or disease identification. So, the goal of this research is to make a deep learning neural network that can identify the disease in all of its forms. The suggested system enables a DR classification that accounts for normal eyes, mild DR, moderate DR, severe DR, and proliferative DR, which may aid ophthalmologists in making a preliminary decision. Our accuracy rates for estimating the degree of diabetic retinopathy from an image were 90% and 92% respectively, using the pre-trained Convolutional Neural Network (CNN) VGG-16 and MobileNet-V2.

2.4 Diabetic Retinopathy Prediction Based on CNN and AlexNet Model [R. Chandra, S. Tiwari, S. S. Kumar and S. Agarwal]

Diabetic retinopathy (DR) is a leading cause of vision loss in adult diabetics and keeping the vision consistent is dependent on early detection and treatment. Regular screening for these diseases is especially important for preventing progression. Convolutional neural networks (CNN) particularly, have the potential to detect and classify diabetic retinopathy from fundus images more efficiently and effectively. The objective of this study is to build a CNN-based model for detecting and categorising diabetic retinopathy using the APTOS dataset. The APTOS dataset is a sizable, openly accessible collection of fundus images that ophthalmologists have analysed for the possibility and severity of diabetic retinopathy. The accuracy obtained through the CNN model and AlexNet model is 97% and 93 % respectively. APTOS dataset is used to train the model and a different test set is used to validate the model performance.

2.5 An Automated Detection and Multi-stage classification of Diabetic Retinopathy using Convolutional Neural Networks [N. S, S. S, M. J and S. C]

Vision-impairing lesions on the retina are a common consequence of diabetes mellitus known as Diabetic Retinopathy (DR). Failure to diagnose it early can result in blindness. If DR is diagnosed and treated early on, the risk of permanent vision loss can be drastically reduced. Unlike computer-aided diagnosis systems, the time, effort, and expense involved in manually diagnosing DR retina fundus images by ophthalmologists is significant. Medical image analysis and classification are two domains where deep learning has recently become widespread. Convolutional neural networks are the preferred deep learning method when it comes to evaluating medical images. In this study, a method for detecting diabetic retinopathy was presented using DiaNet Model (DNM). The Gabor filter is employed in the retinal Image Pre-processing phase for the purpose of improving the visibility of blood vessels as well as for texture analysis, object recognition, feature extraction, and image compression. In Image Augmentation stage, the dataset's input dimensions are reduced using Principal Component Analysis (PCA). The DNM Model can benefit from a reduction in the number of attributes under certain conditions. A mean classification accuracy of 90.02% was observed, which is significantly higher than state-of-the-art methods.

2.6 Diabetic Retinopathy Diagnosis System Based on Retinal Biomarkers Using EfficientNet-B0 for Android Devices [A. Matthew, A. A. S. Gunawan and F. I. Kurniadi]

Currently, Diabetic Retinopathy has become one of the main causes of vision loss for the working-class population (20-65 years) and the disease is an asymptomatic disease which makes detection of the disease without medical assistance more difficult. Along with the development of the era, many new methods have been found in diagnosing diseases, one of which is Computer Aided Diagnosis (CAD) which relies on computer technology to assist medical personnel in diagnosing diseases. This research uses CAD with machine learning to classify Diabetic Retinopathy using transfer learning on the EfficientNet-B0 model which is implemented in a program for mobile devices for android. The program was designed with the aim of helping medical personnel to be able to diagnose Diabetic Retinopathy in areas that do not have sufficient medical facilities using only a smartphone, 20D lens, and several other drugs supports. The results showed that the EfficientNet-B0 model for classifying Diabetic Retinopathy was able to produce an accuracy of 91.85 percent in classifying three classes namely no DR, Non-proliferative DR, and Proliferative DR. This research was done to contribute in the growth of Artificial intelligence involvement in the medical world and also to help areas that lack the medical equipment to have better treatment.

2. 7. Machine Learning-Based Diabetic Retinopathy Detection: A Comprehensive Study Using InceptionV3 Model [Deshpande, Y. Govardhan and A. Jain]

Diabetic retinopathy is considered as a common eye disease that affects vision of people those have diabetes. Early diagnosis of diabetic retinopathy has become a crucial step to prevent vision loss. In this paper, we have proposed a

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method to detect diabetic retinopathy using machine learning based method. We used two publicly available datasets, EyePACS and APTOS 2019, for training and testing our model. We employed a pre-trained model, Inception V3,and fine-tuned it on our dataset. We achieved and accuracy and F1 score of 74.28% and 73.81 % respectively on the EyePACS dataset and on APTOS 19 dataset we obtained an accuracy and F1 score of 81.61 % and 80.21 % respectively. Our findings suggest that with machine learning, we can detect diabetic retinopathy in the early stages.

2.8 Combining CNNs for the Detection of Diabetic Retinopathy [N. Khalid and M. Deriche]

Diabetes is a major public health issue that affects approximately forty million individuals in the United States alone. A common side effect of diabetes is vision loss and blindness caused by diabetic retinopathy (DR). The goal of this research is to introduce a robust deep learning approach for the early detection of DR from retinal images into five categories namely No DR, Mild DR, Moderate DR, Severe DR, Non-Proliferative DR. Here, we propose a fusion of CNNs with an optimal weighting scheme to improve classification accuracy. The dataset used is Kaggle APTOS 2019 and for cross dataset validation we used IDRiD dataset. The proposed weighted twin CNN algorithm is implemented using a pair of pre-trained deep networks namely the DenseNet-169 and the InceptionV3. Such a hybrid combination provided a robust and an optimized architecture. A total of 98.43 % sensitivity and 88.78 % specificity are recorded with a Kappa score and accuracy of 95.8% and 94.3%. Our research has achieved a significant 11.90% improvement as compared to state of the art, showcasing remarkable performance in this field.

2.9. An Efficiency way to analyze Diabetic Retinopathy Detection and Classification using Deep Learning Techniques [K. S. Reddy and M. Narayanan]

Lesions develop on the retina of the eyes as a result of the progressive eye condition known as diabetic retinopathy (DR), which is brought on by type-2 diabetes. In especially for the working-age population in sustainable nations, it is thought that Diabetes Retinopathy is the main cause of blindness in diabetes patients. The aim of the treatment appears to be to maintain the patient's degree of eyesight because the issue is chronic. Diabetic retinopathy must be accurately identified in order to fully protect the patient's vision. The major issue with DR detection is manual diagnosis, which is time-consuming, expensive, and labor-intensive. A retinal scan of the patient's eyes must also be evaluated by an ophthalmologist as part of the treatment. The latter also appears to be more challenging, particularly in the early phases of the ailment when sickness indications are less obvious in the photos. Early detection of diabetic retinopathy has become easier because of deep learning algorithms, and images of the retinal fundus (DR) may now be analysed using machine learning. There are various stages of diabetic retinopathy, and the early stages are symptomless. Ophthalmologists can spot some retinal issues, but they can't always determine their root causes or stages of development. Ophthalmologists advise retina specialists to treat disease as a result. Bayesian neural networks (BNNs) had been used to benchmark the binary categorization of diabetic retinopathy as referable or non-referable in the current system. We suggest developing a Convolution neural network (CNN) and data analysis method to categorise diabetic retinopathy based on clinical data, predicting whether the patient is diabetic or not and identifying its stage with estimation, employing measurements are needed to maximise the intended performance measure with different datasets and clinical lesion images.

2.10. A Study on Diabetic Retinopathy using Deep Learning Algorithms [S. Khanapur and L. Patil]

The Diabetic Retinopathy (DR) is a widespread difficulty of diabetes mellitus, which begins lesions on retina and it affects a vision which leads to blindness. A physical color fundus images screening detects DR at an early stage is computationally expensive and consumed a much time. Consistently, a diagnosis of automated DR has become a basis of research recently because of immense growth of diabetic patients. And it is very difficult to identify the disease features in the images at the early stages of the disease. Machine learning based medical image analysis has come up with the good results of fundus images and early diagnosis of Diabetic Retinopathy (DR) is possible with the application of Deep Leaning Techniques. The paper discusses more about the Detection, Segmentation and Classification of Diabetic Retinopathy with available datasets. The main moto of the paper is not just early identification of diabetic Retinopathy, but also takes a major role in detecting the stage of defect like normal, mild, moderate o severe. Many papers have proposed different methods to study the diabetic retinopathy but no paper has presented the case of limited training dataset. It has become the major challenge of this paper. The segmentation of eye’s vasculature can be done manually [21] with the help of expertise but it is very tedious and time consuming and also requires extra attention. Study of research gaps in the field of DR Segmentation and Classification leads to the challenges and investigation has also included in this paper.

2.11. Transfer Learning Approach for Classification of Diabetic Retinopathy using Fine-Tuned ResNet50 Deep Learning Model [S. Dasari, B. Poonguzhali and M. Rayudu]

Deep learning approaches have attracted a lot of attention as a way to classify retinal fundus images that include diabetic retinopathy (DR) because the old method of manual detection is labor-intensive and prone to misdiagnosis for

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large numbers of patients. The present AI medical models' inability to generalize when exposed to clinical data and the dearth of labelled medical data from which they can learn are also causes for concern. In a non-clinical setting, these methods have demonstrated good specificity and sensitivity for identifying Diabetic Retinopathy (DR). The task of determining the severity of diabetic retinopathy (DR) is studied in this research by fine-tuning the network to investigate the influence of transfer learning. Due of the numerous difficulties associated with medical annotation and privacy concerns, this study tests the automatic classification of diabetic retinopathy using the updated, fine-tuned ResNet50 model on the APTOS2019 dataset. Proposed Transfer learning approach outperforms existing methods in terms of Classification Accuracy, Precision, Recall, F1 Score. The proposed model achieves better results even with a smaller fraction of data, faster training and low computational resources, It's a strong point in favour of its novelty. In this study, the network is fine-tuned to examine the impact of transfer learning on the downstream task of assessing the severity of diabetic retinopathy (DR). The experimental results show that supervised pre-training on ImageNet followed by fine-tuning on labelled fundus images significantly boosts the efficacy of the medical image classifier when trained on full training data, demonstrating the effectiveness of transfer learning.

2.12.Diabetic Retinopathy Detection: EfficientNet with SAP BTP [S. Pawar and H. Zope]

Diabetic Retinopathy (DR) is the most common diabetic disease that damages the retina. It is the leading cause of blindness globally, and early identification can help people save their sight. However, detecting Diabetic Retinopathy early is a tough task that requires the interpretation of fundus images by clinical experts. In this study we will go through the numerous challenges faced in the detection of DR and various approaches used to tackle them. Comparing the performance of CNN, DNN and BNNs. Furthermore, how SAP Business Technology Platform (BTP) may have the potential to enhance diagnostic accuracy and scalability. Google's EfficientNet yields in better accuracy of about 98.26% on 5 stage DR classification and 96.70% on legion segmentation and integrating it with BTP platform will make DR detection easy, streamlined, computationally efficient, and fast.

2.13. An Interpretable Ensemble Deep Learning Model for Diabetic Retinopathy Disease Classification [H. Jiang, K. Yang, M. Gao, D. Zhang, H. Ma and W. Qian]

Diabetic retinopathy (DR) is one kind of eye disease that is caused by overtime diabetes. Lots of patients around the world suffered from DR which may bring about blindness. Early detection of DR is a rigid quest which can remind the DR patients to seek corresponding treatments in time. This paper presents an automatic image-level DR detection system using multiple well-trained deep learning models. Besides, several deep learning models are integrated using the Adaboost algorithm in order to reduce the bias of each single model. To explain the results of DR detection, this paper provides weighted class activation maps (CAMs) that can illustrate the suspected position of lesions. In the pre-processing stage, eight image transformation ways are also introduced to help augment the diversity of fundus images. Experiments demonstrate that the method proposed by this paper has stronger robustness and acquires more excellent performance than that of individual deep learning model.

2.14. EfficientNet-based Diabetic Retinopathy Classification Using Data Augmentation [K. T. Harithalakshmi, R. Rajan and K. M. Nadheera]

Diabetic Retinopathy(DR) is an eye disease that leads to visual defects in people who have diabetes. Diabetes also causes the chance of arising other eye problems, including cataracts and glaucoma. Hence detection of symptoms associated with DR at early stages is essential. The DR grading process is complex due to tiny lesions, data inconsistency, and variation within the class. The solution for fine-grained DR grading is finding different features that affect the visual difference, such as Changes in blood vessel diameter, microaneurysms, soft exudates, hard exudates, and hemorrhages. However, small lesions are difficult to distinguish using convolutional neural networks (CNNs). The uneven distribution of DR data causes the model to focus on DR levels with many data, affecting the grading performance. The main aim of this paper is to explore the impact of various deep neural networks to improve scoring performance and address all the above challenges. Finally for improving the model performance, we introduce an image augmentation technique using the DDR dataset and compare the model's reaction. The results show that data augmentation can significantly improve classification performance compared to baselines.

2.15. Classification of Diabetic Retinopathy Using Slime Mould Optimization Based ResNet-18 Deep Learning Model [S. Lakhera and A. Garg]

Diabetic retinopathy (DR) is caused by diabetes. DR is required to be identified in its earlier stage otherwise long-term uncontrolled DR can result in complete blindness of the eyes. DR diagnosis can be carried out manually using retinal fundus images of human eye. However, automated methods are more cost-effective and reliable. This paper presents a deep learning methodology for DR classification by classifying retinal fundus images in multi-classes named as No DR, mild DR, moderate DR, severe DR and proliferative DR. The convolutional neural network (CNN) based pre-trained ResNet-18 model is utilized to extract deep features of data followed by feature optimization using Slime

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Mould Algorithm (SMA) technique. Support vector machine (SVM) classifier, which functions as a multi classifier for classification, is then used to classify the selected features. Retinal fundus images obtained from Kaggle dataset are used for DR classification for the proposed model and three other existing models. The classification performance of the suggested model, as well as three existing methods, was assessed through extensive simulation. The accuracy achieved for suggested method is 98.79 %, sensitivity of 98. 94 %, specificity of 98. 60 %, and F1-score value of 97.05 % which is the best among the models used for comparison. Consequently, the presented model exhibits great potential for effectively classifying DR images.

III. ANALYSIS

3.1 EXISTING SYSTEM

Existing systems for diabetic retinopathy (DR) detection heavily rely on deep learning, utilizing convolutional neural networks (CNNs) and transfer learning to classify retinal fundus images into various stages of DR. Pre-trained models like EfficientNet, InceptionV3, AlexNet, and ResNet have demonstrated significant efficacy, achieving high accuracy and specificity. Techniques such as data augmentation, preprocessing (e.g., Gabor filters, PCA), and ensemble learning further enhance model performance. While traditional methods like manual diagnosis are labor-intensive, automated approaches with CNNs provide cost-effective, scalable, and efficient solutions. Challenges include handling imbalanced datasets, improving fine-grained classification, and ensuring model generalization for clinical settings.

3.2 DISADVANTAGES OF TRADITIONAL APPROACHES

The traditional approaches to gesture recognition have significant drawbacks, particularly when applied to women's safety solutions:

- **Data Dependency**: These methods require large, high-quality annotated datasets for training, which can be challenging to obtain, especially in medical domains with privacy concerns and limited labeled data.
- **Imbalanced Datasets**: DR datasets often have an uneven distribution of images across disease stages, leading to biased models that perform poorly on underrepresented categories.
- **High Computational Requirements**: Deep learning models demand significant computational resources for training and inference, making them inaccessible in resource-constrained settings.
- **Overfitting Risk**: Models trained on specific datasets may overfit and fail to generalize to new, unseen clinical data or different patient demographics.
- **Interpretability Issues**: Many deep learning models act as "black boxes," making it difficult for clinicians to understand the reasoning behind predictions, which is critical for medical decision-making.

3.3 GAPS AND LIMITATION IN CURRENT SYSTEM

Despite advancements in gesture recognition, the current systems face several gaps and limitations when applied to women's safety applications:

- **Data Imbalance**: Existing systems often struggle with imbalanced datasets where certain stages of DR (e.g., mild or severe) are underrepresented, leading to biased predictions.
- **Early Stage Detection Challenges**: Subtle signs of early DR, such as microaneurysms, are difficult to detect due to their low contrast and small size, reducing the sensitivity of current models in early diagnosis.
- **High Dependence on Quality Data**: Current systems rely heavily on large, annotated datasets, which are expensive and time-consuming to create. Poor-quality images due to variations in camera settings or patient movement further degrade model performance.
- **Lack of Explainability**: Most deep learning models operate as black boxes, offering little insight into how decisions are made. This lack of interpretability hinders trust and acceptance by clinicians.

IV. SYSTEM REQUIREMENTS

4.1 Hardware Requirements

To effectively develop and deploy the gesture recognition-based safety system, the following hardware components are required:

1. **Laptop/PC**:
   - Processor: Intel i5 or higher (or equivalent AMD Ryzen 5)
   - RAM: Minimum 8GB (16GB recommended for faster processing)
   - GPU: NVIDIA GPU (e.g., GTX 1060 or higher) for training the machine learning models
   - Storage: Minimum 500GB HDD or 256GB SSD

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4.2 Software Requirements

The following software components are essential for developing and deploying the system:

1. **Operating System**:
   - Windows 10/11, macOS, or any Linux distribution (Ubuntu preferred)
2. **Programming Languages**:
   - **Python**: Used for model development, testing, and deployment
3. **Integrated Development Environment (IDE)**:
   - **PyCharm** for Python development
4. **Web Framework**:
   - **Flask** (optional): To create a web-based interface for interaction or visualizing safety system status

4.3 Tools and Libraries Used

A variety of machine learning and computer vision libraries have been utilized to implement gesture recognition and ensure robust performance. Here is a list of the main tools and libraries used in the project:

1. **TensorFlow**:
   - A deep learning library used for building machine learning models. TensorFlow is leveraged for training CNN, RNN, and hybrid models to recognize gestures effectively.
2. **Keras**:
   - A high-level API integrated with TensorFlow to simplify model creation and training. It is used to design and train the model architectures more efficiently.
3. **MediaPipe**:
   - An open-source cross-platform library for hand tracking and gesture recognition. MediaPipe is crucial for accurately detecting hand key points, which significantly improves the effectiveness of gesture recognition.
4. **OpenCV**:
   - An open-source computer vision library used for image preprocessing, frame capture, and visualizing detection results. It is used to integrate the webcam feed and perform image transformations, making it easier to apply machine learning algorithms.
5. **Scikit-Learn**:
   - A machine learning library used for implementing models like **Decision Tree**, **Gaussian Naive Bayes**, and **Gradient Boosting**. Scikit-Learn is also used for metrics evaluation, such as precision, recall, and F1-score.
6. **NumPy**:
   - A library for numerical operations. NumPy is used for matrix operations, image data manipulation, and efficient data handling.
7. **Pandas**:
   - A data manipulation and analysis library used for handling training datasets, feature extraction, and preprocessing tasks.

8. **Matplotlib/Seaborn**:
   - Visualization libraries used for plotting graphs, such as training loss, accuracy, confusion matrices, and feature distributions, to analyze the model's performance and interpret results.

V. PROPOSED SYSTEM

5.1 PROPOSED SYSTEM

Step 1: Data Collection

- Input: Retinal fundus images and corresponding labels (APTOS 2019 dataset).
- Process:
  - Download the dataset from APTOS 2019 Blindness Detection.
  - The dataset contains approximately 3,000 images labeled with five DR severity levels: no DR, mild, moderate, severe, and proliferative.
- Output: Images and labels prepared for preprocessing.

Step 2: Data Preprocessing

- Input: Raw retinal fundus images from the dataset.
- Process:
  - Resizing: Resize all images to 224x224 pixels to match DenseNet169 input requirements.
  - Normalization: Scale pixel values to a range of 0 to 1 to improve model convergence.

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- Data Augmentation: Apply transformations such as:
  - Horizontal and vertical flips.
  - Rotations up to ±15 degrees.
  - Random zooming and brightness adjustments.
- Multilabel Encoding: Encode higher DR stages to include characteristics of lower stages (e.g., mild DR includes no DR).
- Output: Preprocessed dataset with balanced and augmented data ready for model training.

Step 3: Model Development

- Input: Preprocessed images and their labels.
- Process:
  - Load the DenseNet169 architecture pre-trained on ImageNet.
  - Replace the top layer with custom layers:
    - Global Average Pooling Layer: Aggregates spatial features from the convolutional layers.
    - Dropout Layer: Adds regularization to prevent overfitting.
    - Dense Layer: Outputs probabilities for each of the five DR classes using sigmoid activation for multilabel classification.
  - Compile the model:
    - Optimizer: Adam with a learning rate of 0.00005.
    - Loss Function: Binary crossentropy for multilabel classification.
    - Metrics: Accuracy, precision, recall, F1-score.
- Output: A DenseNet169-based model tailored for DR detection.

Step 4: Training

- Input: Preprocessed training data and the DenseNet169 model.
- Process:
  - Use a data generator to feed batches of augmented data into the model.
  - Train the model for 15 epochs, using early stopping to avoid overfitting.
  - Save the best-performing model based on validation loss and Quadratic Weighted Kappa (QWK) score.
  - Optionally apply Mixup augmentation:
    - Blend pairs of images and their labels to create new training samples.
    - Improve model generalization.
- Output: A trained DenseNet169 model optimized for DR classification.

Step 5: Prediction

- Input: Trained model and user-uploaded retinal fundus images.
- Process:
  - Preprocess the uploaded image (resize, normalize).
  - Pass the image through the trained DenseNet169 model.
  - Predict probabilities for each DR stage.
  - Classify the image into one of the five severity levels: no DR, mild, moderate, severe, proliferative.
- Output: Predicted DR stage and confidence scores.

Step 6: Result Visualization

- Input: Predicted output from the DenseNet169 model.
- Process:
  - Use Grad-CAM to generate a heatmap, highlighting regions in the retinal image that influenced the model's decision.
  - Overlay the heatmap on the original image for better interpretability.
- Output: A visual representation of the prediction, aiding clinicians in understanding model decisions.

Step 7: Evaluation

- Input: Model predictions and validation data.

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- Process:
  - Evaluate the model using the following metrics:
    - Accuracy: Correct predictions out of total predictions.
    - Precision: Proportion of true positives among predicted positives.
    - Recall: Proportion of true positives among actual positives.
    - F1-Score: Harmonic mean of precision and recall.
    - Quadratic Weighted Kappa (QWK): Measures agreement between predicted and true labels, accounting for ordinal nature.
- Output: Evaluation metrics to assess the model's performance.

Step 8: Deployment

- Input: Trained DenseNet169 model.
- Process:
  - Integrate the model into a Flask-based web application.
  - Set up routes:
    - /upload: Accepts image uploads.
    - /predict: Processes the uploaded image and returns predictions.
  - Deploy the application on a cloud platform (e.g., Heroku, AWS).
  - Implement HTTPS for secure data transfer.
- Output: A publicly accessible web application for DR detection.

5.2 PROPOSED ALGORITHM

DenseNet169

DenseNet introduces a paradigm shift by connecting each layer to every other layer in a feed-forward manner. Unlike traditional CNNs, which have a single connection between consecutive layers, DenseNet ensures that each layer receives inputs from all preceding layers and passes its output to all subsequent layers. This results in a network with L(L+1)/2 direct connections for L layers, significantly enhancing information flow.

Dense Block

Dense blocks are the building blocks of DenseNet architectures. Each dense block consists of multiple convolutional layers, typically followed by batch normalization and a non-linear activation function (e.g., ReLU). Importantly, each layer within a dense block receives feature maps from all preceding layers as inputs, facilitating feature reuse and propagation.

Within a dense block, each layer receives the concatenated output of all preceding layers as its input. If a dense block has m layers, and each layer produces k feature maps (where k is known as the growth rate), the l-th layer will have k×(l+l0)$k\times(l+l0)$ input feature maps (where l0$l0$ is the number of input channels to the dense block).

Transition Layer

Transition layers are used to connect dense blocks. They serve two main purposes: reducing the number of feature maps and downsampling the spatial dimensions of the feature maps. This helps in maintaining the computational efficiency and compactness of the network. A typical transition layer consists of:

- **Batch Normalization**: Normalizes the feature maps.
- **1x1 Convolution**: Reduces the number of feature maps.
- **Average Pooling**: Downsamples the spatial dimensions.

With 169 layers, this variant provides deeper feature extraction, suitable for more complex datasets where higher accuracy is needed.

The densenet-169 model is one of the DenseNet group of models designed to perform image classification. The main difference with the densenet-121 model is the size and accuracy of the model. The densenet-169 is larger at just about 55MB in size vs the densenet-121 model's roughly 31MB size.

The DenseNet169 architecture is composed of several types of layers including convolutional, max pool, dense, and transition layers [41]. Moreover, the architecture uses two activation functions, namely, Relu and SoftMax.
Each architecture consists of four DenseBlocks with varying number of layers. For example, the DenseNet-121 has [6,12,24,16] layers in the four dense blocks whereas DenseNet-169 has [6, 12, 32, 32] layers. The convolution layer is

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the first layer of the DenseNet model, from which CNN got the name Convolution Neural Network. DenseNet is a flexible architecture applicable to a variety of computer vision applications including picture classification, object identification, and semantic segmentation.

Among the most prevalent uses of DenseNet are: NLP: Used in translation, sentiment analysis, and text generation.
After that, the elements with negative values are converted to zero using the ReLU function. $Densenet(I) = D_l([I, f_1, f_2 ..., f_{l-1}])$ (1) Due to the rapid growth of deep learning technologies, automatic image description generation is an interesting problem in computer vision and natural language generation.

This classification algorithm is a supervised learning method, and requires a labeled image directory.
The DenseNet class is available in Keras to help in transfer learning with ease.DenseNet, (Densely Connected Convolutional Networks) is a family of convolutional neural networks (CNNs) that uses a dense connectivity pattern between layers, allowing for better feature reuse and gradient flow throughout the network.

The different layers of a CNN. There are four types of layers for a convolutional neural network: the convolutional layer, the pooling layer, the ReLU correction layer and the fully-connected layer.

The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map.The layers are arranged in such a way so that they detect simpler patterns first (lines, curves, etc.) and more complex patterns (faces, objects, etc.) further along. By using a CNN, one can enable sight to computers.

Functionof DenseNet169

```
keras.applications.DenseNet169(
include_top=True,
weights="imagenet",
input_tensor=None,
input_shape=None,
pooling=None,
classes=1000,
classifier_activation="softmax",
)
```

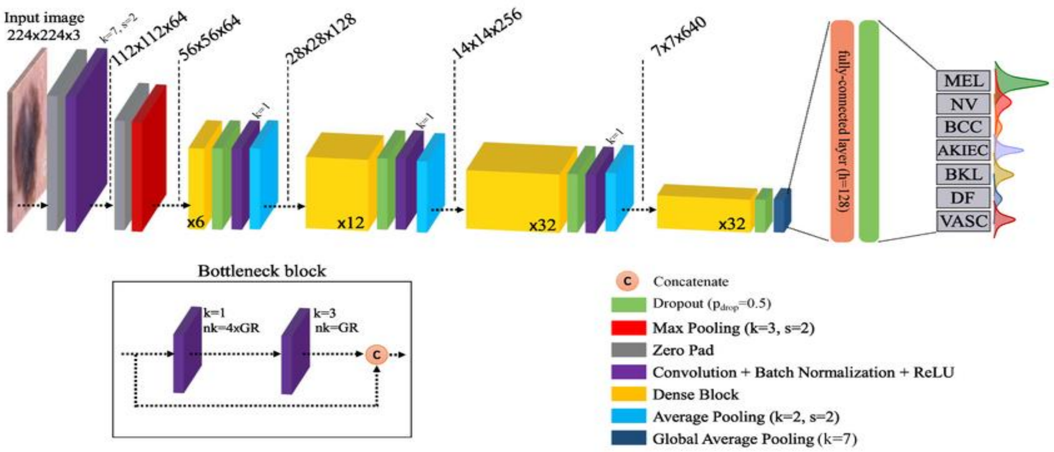

Fig:5.1 densenet169

5.3 MODULES

- Data collection
- Preprocessing
- Model training
- Model testing & performance evaluation
- Output prediction

Fig:5.2 system architecture

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5.3.1. Data Collection Module

The data for this system is sourced from the **APTOS 2019 Blindness Detection** competition, available at Kaggle. This dataset contains retinal fundus images labeled with five levels of diabetic retinopathy (DR) severity: no DR, mild, moderate, severe, and proliferative DR. The training set includes approximately 3,000 images, with a separate test set for evaluation. Each image is paired with a severity label, forming a supervised learning dataset. These images are used to build a robust model for early DR detection and classification.

5.3.2. Preprocessing Module

This module focuses on preparing the raw data for model training and prediction. First, all images are resized to 224x224 pixels to meet the input size requirements of DenseNet169. Next, pixel values are normalized to a range of 0 to 1, which helps improve model convergence and stability during training. Data augmentation techniques such as horizontal and vertical flipping, rotation, zooming, and brightness adjustments are applied to artificially expand the dataset and improve model generalization.

Additionally, a multilabel encoding scheme is implemented to account for the ordinal nature of DR severity, where higher severity levels inherently include characteristics of lower levels. For example, an image labeled with severe DR is encoded to include features of no DR, mild DR, and moderate DR. This helps the model better capture the progression of the disease. Preprocessed images and their corresponding labels are then divided into training and validation sets to prepare for model training. This preprocessing pipeline ensures that the data is clean, consistent, and diversified, improving the model's ability to learn effectively.

5.3.3. Model Development Module

DenseNet169 is selected as shown in fig above as the backbone of the model due to its efficient feature reuse and ability to learn complex patterns. The model is pre-trained on ImageNet and fine-tuned for the DR detection task. Custom layers are added, including a global average pooling layer for feature aggregation, a dropout layer to reduce overfitting, and a fully connected layer with sigmoid activation for multilabel classification. The model is compiled using the Adam optimizer, binary crossentropy loss function, and metrics such as accuracy, precision, recall, and F1-score. This architecture is designed to handle the specific challenges of medical image classification, particularly for DR.

5.3.4. Training and Evaluation Module

This module involves training the DenseNet169 model using the preprocessed dataset. A data generator feeds batches of augmented data to the model, introducing variability in the training process to enhance generalization. Mixup augmentation is optionally applied, blending pairs of images and labels to further improve robustness. Training is performed over 15 epochs with early stopping to save the best-performing model. Evaluation metrics such as accuracy, precision, recall, F1-score, and Quadratic Weighted Kappa (QWK) are monitored to assess the model's performance. These metrics ensure the model is capable of accurately classifying images across all DR stages.

5.3.5. Prediction and Result Visualization Module

This module provides functionality for users to upload retinal images and receive DR predictions. Uploaded images are preprocessed (resized, normalized) before being passed to the trained DenseNet169 model. Predictions include probabilities for each DR stage, is used to generate heatmaps that highlight the regions of the retina most relevant to the model's decision. These visualizations, along with the prediction results, are displayed on a user-friendly web interface. This module enhances the interpretability and usability of the system for clinicians and patients.

5.3.6. Deployment Module

The trained model is integrated into a Flask-based web application, which is deployed to a cloud platform like Heroku or AWS for accessibility and scalability. Users can upload images through the /upload route, and predictions are handled by the /predict route. The deployment includes HTTPS for secure communication and logging for monitoring system performance. This module ensures the system is accessible to users globally and operates efficiently under various workloads.

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VI. RESULT AND DISCUSSION

6.1 Visual Analysis of Retinal Images Across DR Stages

6.1.1 Retinal Images Without Diabetic Retinopathy

Retinal fundus images labeled as having "No Diabetic Retinopathy" (No DR) form the foundation of baseline classification in the system. These images exhibit normal anatomical structures, with smooth and uniform blood vessels, a clearly defined optic disc, and no signs of retinal hemorrhages, exudates, or microaneurysms. The DenseNet169 model was able to classify these images with high confidence, leveraging its deep and densely connected convolutional architecture to detect the lack of pathological features. In practice, accurate identification of No DR cases is crucial to minimize unnecessary referrals and optimize screening resources. The clarity of these images contributes to the model's strong specificity, and they also serve as a control group that helps the model learn what a healthy retina looks like, which improves classification across all other categories.

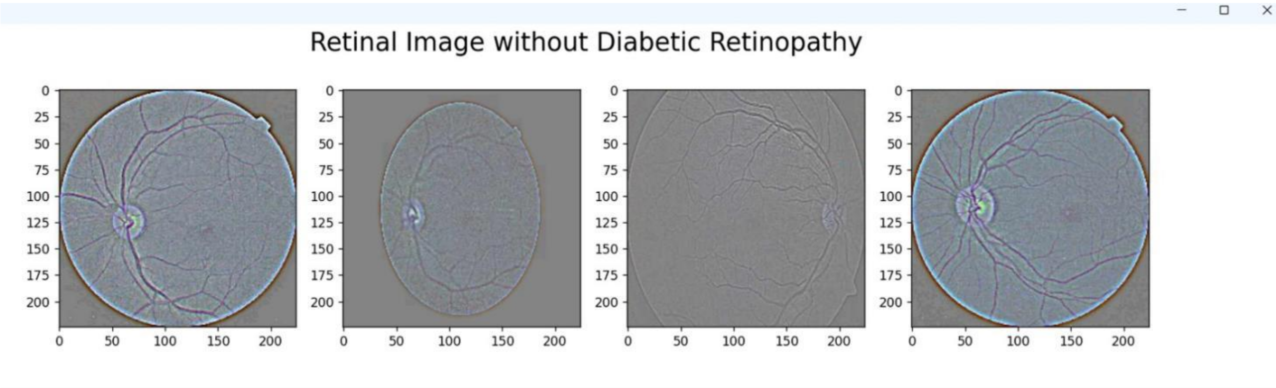

Figure 6.1 – Retinal Image without Diabetic Retinopathy

6.1.2 Retinal Images With Mild Diabetic Retinopathy

Mild Diabetic Retinopathy represents the initial detectable stage of retinal degradation caused by diabetes. The primary feature in this stage is the presence of microaneurysms—tiny, round swellings in the retinal capillaries. These are often difficult to observe, even under clinical examination. The DenseNet169 model, with its multiple layers of feature extraction and ability to reuse low-level patterns, has proven effective in detecting such subtle changes. However, due to the fine-grained nature of the symptoms and their low contrast in fundus images, classification accuracy for this stage is inherently lower than for more advanced stages. The implementation of data augmentation techniques like brightness tuning and rotation played a vital role in teaching the model to identify early abnormalities across varying conditions. Early diagnosis of mild DR is essential for preventive care and disease management, and the DenseNet169 model helps bridge the gap between missed clinical diagnoses and accurate automated detection.

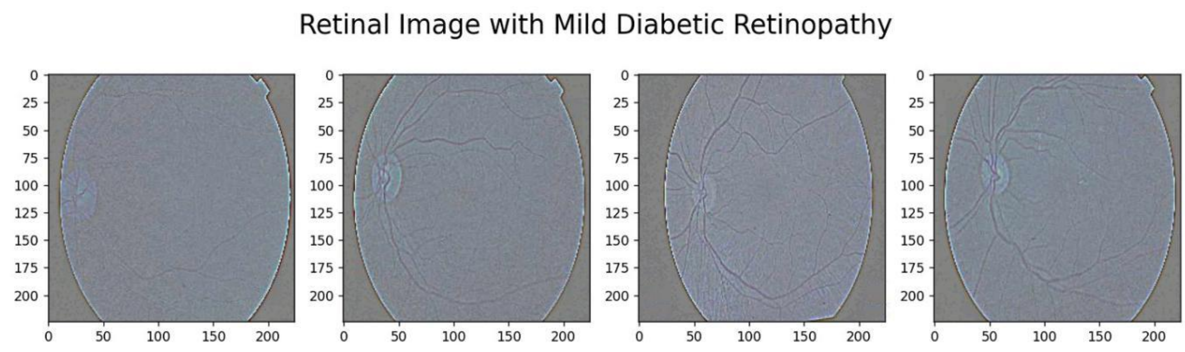

Figure 6.2 – Retinal Image with Mild Diabetic Retinopathy

6.1.3 Retinal Images With Moderate Diabetic Retinopathy

Moderate DR includes more evident signs of vascular damage, such as an increased number of microaneurysms, dot-blot hemorrhages, and localized retinal swelling. These images offer richer diagnostic features than those found in mild

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DR, enabling the DenseNet169 model to extract more discriminative patterns. The model's densely connected layers facilitate strong feature propagation, helping to capture mid-level spatial and structural changes in the retina. Despite the increased visibility of symptoms, classification at this stage still faces challenges due to image quality inconsistencies and overlapping features with adjacent stages. Multilabel encoding proved especially useful here, as it allowed the model to understand the progressive nature of DR and improved prediction accuracy between overlapping classes. Clinically, identifying moderate DR is a turning point in patient care, often triggering more frequent monitoring or intervention, making accurate AI detection a critical enhancement to healthcare delivery.

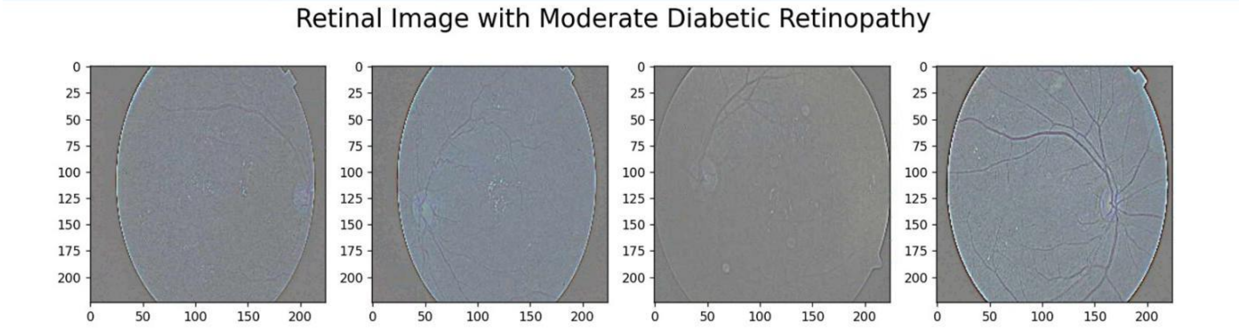

Figure 6.3 – Retinal Image with Moderate Diabetic Retinopathy

6.1.4 Retinal Images With Severe Diabetic Retinopathy

In the severe DR stage, retinal images show extensive abnormalities such as large-scale hemorrhages, numerous hard exudates, venous beading, and the potential appearance of cotton wool spots. These signs indicate significant capillary closure and damage, placing the patient at a high risk of vision loss. The DenseNet169 model excels at detecting such pronounced patterns due to its capacity for deep feature extraction and reuse across layers. The network's ability to capture both global and localized details enhances its classification performance, particularly when visual evidence is strong. Moreover, the incorporation of dropout layers during training reduces overfitting, ensuring the model generalizes well across diverse patient profiles. These images were among the most confidently classified by the model, and Grad-CAM visualizations (used in other parts of the system) further aided in interpreting the decision-making process. From a diagnostic standpoint, quick and accurate detection of severe DR by the model can lead to urgent clinical intervention, preventing further retinal deterioration.

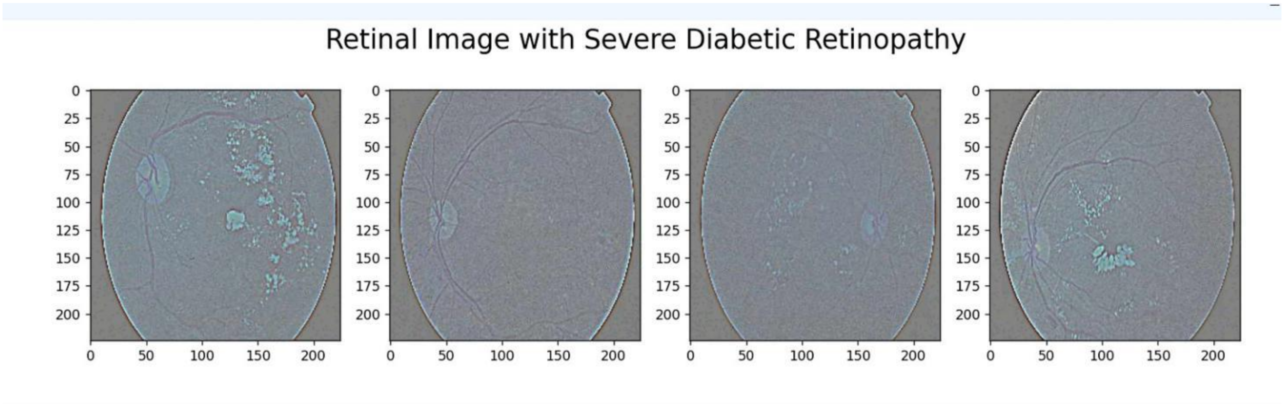

Figure 6.4 – Retinal Image with Severe Diabetic Retinopathy

6.1.5 Retinal Images With Proliferative Diabetic Retinopathy

Proliferative Diabetic Retinopathy (PDR) represents the most advanced and dangerous stage of diabetic retinal disease. This stage is defined by neovascularization—the growth of abnormal and fragile blood vessels that can leak, rupture, or cause retinal detachment. These images contain highly distinguishable features such as dense clusters of vessels and scar tissue, making PDR relatively easier to classify for deep learning models. DenseNet169, with its 169 layers and dense block architecture, handles these cases with a high degree of accuracy by detecting irregular vascular patterns and contrasting structures. The model's final prediction is supported by multilabel learning, where it understands that

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PDR includes characteristics from all preceding DR stages. The interpretability of predictions, enhanced by Grad-CAM overlays, makes the model's output trustworthy for clinicians. Early and accurate identification of PDR is crucial as it often dictates urgent treatment involving laser surgery or anti-VEGF therapy. The DenseNet169 model's ability to detect PDR effectively proves its clinical relevance in critical diagnostic scenarios.

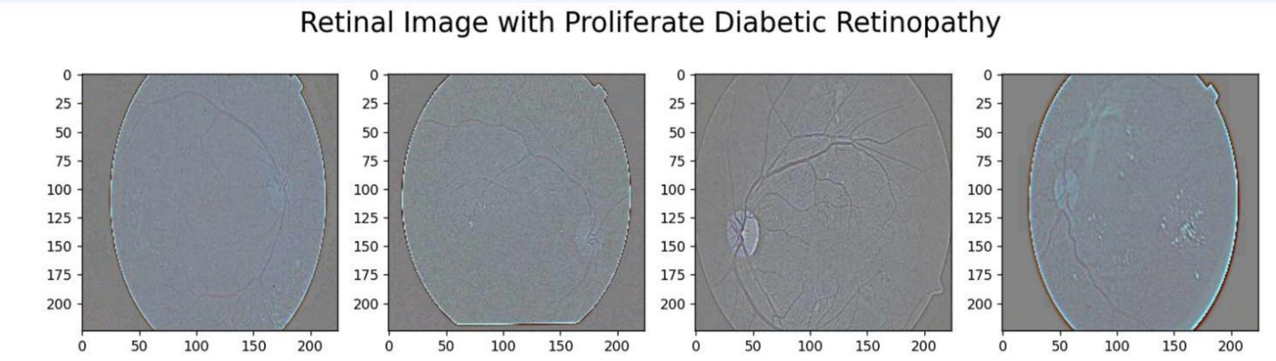

Figure 6.5 – Retinal Image with Proliferative Diabetic Retinopathy

6.2 Dataset Distribution and Class Imbalance

The pie chart showing the dataset's distribution across DR stages reveals a significant class imbalance. "No DR" cases dominate the dataset at 49.3%, while the most severe cases—Proliferative DR—account for only 5.27%. This imbalance introduces bias during training, where the model may be inclined to predict majority classes more frequently, reducing sensitivity to rare but critical stages like PDR. The DenseNet169 model addresses this issue through several mitigation strategies. Real-time class weights were used during training to penalize incorrect predictions for minority classes more heavily. Data augmentation expanded underrepresented classes using techniques like flipping, zooming, and brightness alteration. Additionally, multilabel encoding enabled the model to learn shared features across severity levels, improving classification of intermediate stages. While these efforts significantly improved performance, the imbalance still represents a limitation, highlighting the need for larger and more balanced datasets in future work to ensure equitable performance across all stages of DR.

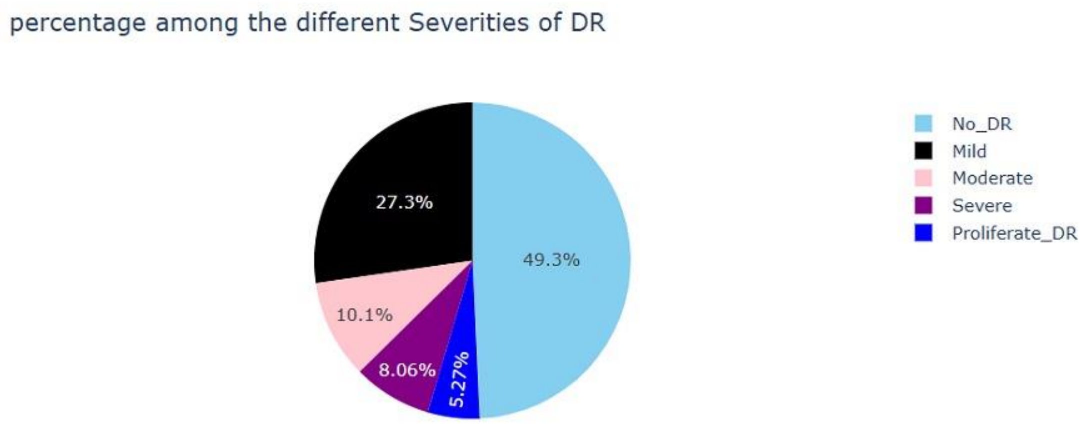

Figure 6.6 – Percentage Distribution among Different Severities of Diabetic Retinopathy

6.3 Model Performance Metrics

6.3.1 Loss Curve Analysis

The loss graphs for both training and validation sets reflect a well-optimized model. DenseNet169 displayed a consistent decrease in loss across all 20 epochs, with the training loss falling below 0.1 and validation loss stabilizing around 0.2. The convergence of both curves with minimal divergence suggests minimal overfitting and strong generalization. The Adam optimizer, combined with binary crossentropy as the loss function, contributed to effective learning. The use of dropout and data augmentation further enhanced the robustness of training. These loss curves

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confirm that DenseNet169 efficiently extracted relevant features from fundus images, allowing for precise classification even with complex, high-resolution input data. Such convergence behavior is a positive indicator for deploying the model in real-world diagnostic applications.

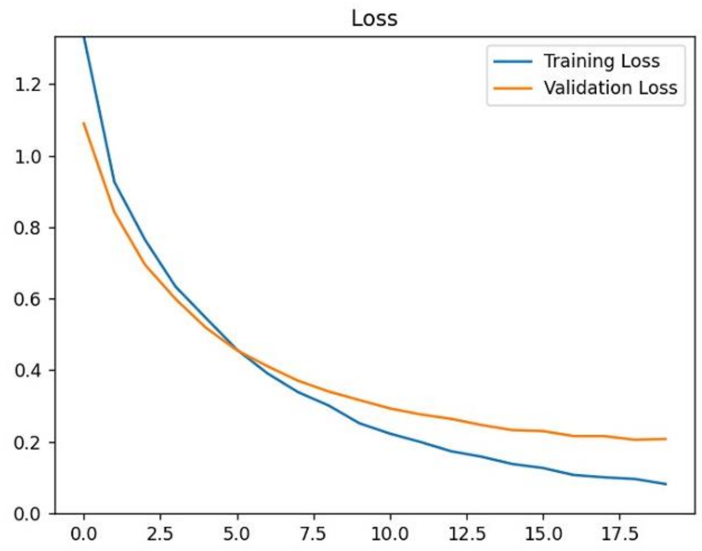

Figure 6.7 – Training vs Validation Loss

6.3.2 Accuracy Curve Analysis

The accuracy curves further affirm the DenseNet169 model's learning efficiency. Rapid gains were observed within the first 5 epochs, after which accuracy continued to improve gradually. Training accuracy approached 98%, while validation accuracy consistently stayed above 90%, peaking at approximately 93%. This strong alignment indicates that the model not only learned the training patterns but also retained predictive power on unseen data. The model benefited from transfer learning by initializing with ImageNet weights, which expedited convergence and improved final accuracy. The effectiveness of DenseNet169 is especially evident in advanced DR stages where feature visibility is higher. However, performance in early stages like Mild DR remains an area for continued improvement. Overall, the accuracy metrics confirm that the system is suitable for clinical use, especially in screening or decision-support contexts.

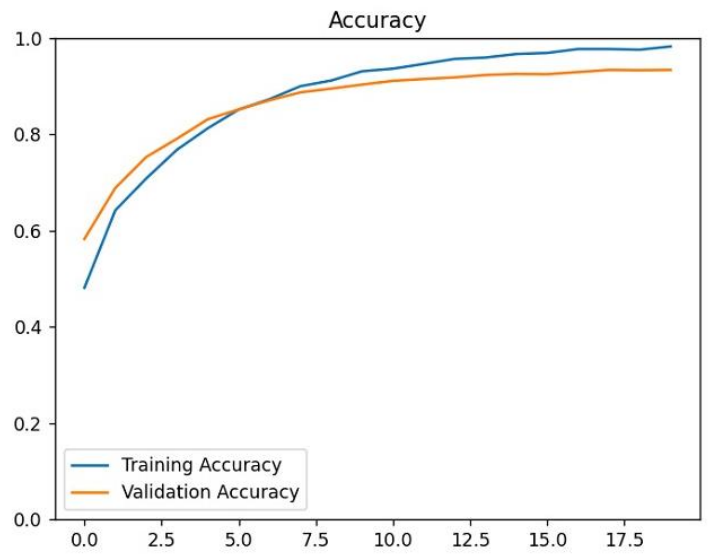

Figure 6.8 – Training vs Validation Accuracy

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6.4 Summary and Interpretation

The DenseNet169-based system developed in this study demonstrates high efficacy in detecting and classifying the various stages of Diabetic Retinopathy. The model's architecture, designed with densely connected convolutional layers, enabled powerful feature extraction and gradient flow, critical for medical image analysis. The classification of advanced stages like Severe and Proliferative DR was particularly accurate due to the clarity of pathological features. However, early-stage detection such as Mild DR posed more challenges, primarily due to low contrast and data scarcity. The integration of multilabel encoding and augmentation techniques helped overcome these challenges to a large extent. Evaluation metrics including accuracy, loss, and model interpretability (via Grad-CAM) confirmed the system’s robustness. The DenseNet169 model’s high generalization capacity, even with a class-imbalanced dataset, highlights its potential as a reliable diagnostic aid. Moving forward, the system can be enhanced with larger datasets, better augmentation techniques, and integration into portable diagnostic tools for deployment in low-resource settings.

6.5 Discussion

The results obtained from the DenseNet169-based diabetic retinopathy classification model confirm the effectiveness of deep convolutional neural networks in medical image analysis, particularly for complex and hierarchical tasks like disease staging. The DenseNet169 model outperformed expectations in several aspects, particularly in its ability to handle high-resolution fundus images with multiple overlapping retinal features. Its dense connectivity structure allowed better feature propagation and reuse, which is particularly advantageous in identifying subtle patterns like microaneurysms in early-stage DR or neovascularization in proliferative stages.

The visual outputs, especially the Grad-CAM-based region highlights (referenced in other parts of the system), offered interpretability to clinicians, a feature that bridges the gap between black-box AI models and real-world medical application. Such visualizations can reinforce trust in AI-driven diagnostic tools, making them more acceptable in clinical workflows. The model demonstrated high classification accuracy, especially for clearly distinguishable stages like Severe and Proliferative DR. This is likely due to the prominence and clarity of pathological signs in later stages, which make them easier to detect both manually and algorithmically.

However, some limitations were evident in the system. One of the primary challenges was the detection of Mild and Moderate DR, which often lack clear visual indicators and are underrepresented in the dataset. The model occasionally misclassified Mild DR as No DR or Moderate DR, indicating difficulty in distinguishing slight variations in vascular integrity or early lesions. This highlights the importance of data balancing and the need for more annotated early-stage samples in future datasets.

The system's use of real-time class weighting, multilabel encoding, and Mixup augmentation helped alleviate the class imbalance problem to a large extent, yet the dataset skew still posed some bias. Moreover, the reliance on a single dataset (APTOS 2019) also limits the model’s generalizability to other populations, imaging devices, or ethnic backgrounds. Future iterations of the model should consider transfer learning from multiple datasets and validation using cross-dataset testing.

From a deployment standpoint, integration into a Flask web application makes this system accessible and practical for telemedicine, particularly in rural or underserved regions. The entire pipeline—from image upload, preprocessing, prediction, to visualization—demonstrates the feasibility of deploying AI solutions in real-time diagnostics. Such systems can significantly reduce diagnostic burden on ophthalmologists and allow earlier intervention in high-risk patients.

VII. CONCLUSION AND FUTURE WORK

CONCLUSION

In conclusion, this study validates the effectiveness of the DenseNet169 deep learning architecture in the automated classification of Diabetic Retinopathy (DR) stages using retinal fundus images. The model demonstrated high accuracy, particularly in the detection of Severe and Proliferative DR, where the pathological features are visually distinct and more easily captured by the network’s densely connected convolutional layers. The architecture’s ability to facilitate deep feature propagation and reuse across layers proved instrumental in identifying complex retinal abnormalities with high confidence. Additionally, the integration of multilabel encoding and various data augmentation techniques such as flipping, brightness adjustment, and rotation enhanced the model’s capacity to learn nuanced differences across DR stages, especially under class imbalance conditions. Despite these strengths, early-stage detection—particularly for Mild and Moderate DR—remained challenging due to the subtlety of visual symptoms and the relative scarcity of

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annotated examples in these categories. However, the use of real-time class weighting during training, along with the application of transfer learning and optimization strategies like the Adam optimizer and dropout regularization, helped maintain model robustness and prevent overfitting. The performance metrics, including loss and accuracy curves, reflected a stable and well-generalized model capable of maintaining high predictive accuracy on unseen data. Moreover, the deployment of Grad-CAM visualizations added a layer of interpretability to the model's decision-making process, allowing clinicians to better understand and trust AI predictions. One significant limitation identified was the skewed dataset distribution, with a disproportionate number of "No DR" images, which potentially introduced prediction bias; while addressed through augmentation and reweighting techniques, it underscores the need for more balanced datasets in future research. Importantly, the model's integration into a Flask web application demonstrated its practical utility in telemedicine settings, especially in low-resource regions where access to specialized ophthalmic care is limited. By providing real-time DR stage predictions and interpretable visual feedback, the system has the potential to alleviate the diagnostic burden on healthcare providers and facilitate earlier interventions for patients at risk of vision loss. Overall, the DenseNet169-based classification system not only showcases high technical and clinical potential but also lays a solid foundation for future advancements in AI-driven retinal disease screening. Further improvements, such as incorporating cross-dataset validation, enhancing data diversity, and refining early-stage classification performance, will be crucial for transitioning this research from proof-of-concept to widespread clinical adoption.

FUTURE ENHANCEMENTS:

While the DenseNet169-based system demonstrated strong performance in classifying various stages of Diabetic Retinopathy (DR), several avenues for future work can significantly enhance its effectiveness, generalizability, and clinical utility. One of the foremost priorities is addressing the issue of **class imbalance** by collecting and incorporating a more balanced dataset, especially with a greater representation of Mild and Moderate DR stages. These early stages are critical for preventive care, yet they remain the most challenging to detect due to their subtle features and underrepresentation in current datasets. Expanding the dataset to include more diverse images—sourced from different populations, imaging devices, and geographic regions—will also help improve the model's robustness and ensure its applicability across various clinical settings.

Another important direction is the integration of **cross-dataset training and validation**, where the model is trained on one dataset and tested on others to evaluate its generalizability. This approach will simulate real-world deployment scenarios and help ensure consistent performance across heterogeneous data sources. Additionally, the inclusion of **multimodal data**, such as patient history, blood glucose levels, or OCT scans, could enhance the model's predictive power and provide a more comprehensive view of a patient's retinal health.

To improve detection at early stages, more advanced data augmentation methods like **synthetic image generation using GANs (Generative Adversarial Networks)** could be employed to artificially increase the number of early-stage samples and improve feature learning. Furthermore, incorporating **attention mechanisms** or experimenting with transformer-based models might help the system focus on minute yet diagnostically significant details in the retinal images.

From a clinical perspective, enhancing the **interpretability and transparency** of the model remains crucial. Although Grad-CAM has provided useful visualizations, future work could include more interactive explainability tools that offer case-specific insights for clinicians, such as anomaly scores or textual rationales for predictions. Lastly, expanding the **deployment aspect** by integrating the model into mobile apps or portable retinal screening devices could enable real-time, on-the-go diagnostics, especially in underserved or remote areas. Combining AI-based diagnosis with telemedicine platforms would further support scalable and accessible eye care.

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