# Diabetic Retinopathy Prediction Using Xception (Deep Learning Approach)

Dr. B.Vanathi[1], Riswant R.G[2], Sandehep S.S[3], Sanjay M[4]
[1]*M.E, Ph.D, SRM Valliammai Engineering College*
[2,3,4] *SRM Valliammai Engineering College*

***Abstract—Prolonged high blood sugar levels induce diabetic retinopathy (DR), a serious eye disorder that damages the retina's blood vessels and, if ignored, can result in blindness or visual loss. Preventing visual impairment requires early detection and action. This study aims to develop a deep learning-based system that automatically detects and classifies DR from retinal fundus images using the Xception architecture. The model provides a quick, inexpensive, and non-invasive screening method by learning to recognize and evaluate the severity of DR by training on a dataset of annotated retinal pictures. This technique may help ophthalmologists diagnose DR early, which would enable prompt treatment and efficient disease management. The experiment shows how deep learning can improve ophthalmology diagnosis speed and accuracy, especially in impoverished regions where specialized care may not be readily available. This project's automated detection model has great promise as a quick, affordable screening tool that can help with early diagnosis and enhance patient outcomes. In the end, this experiment highlights how deep learning is revolutionizing ocular diagnostics and improving diabetic patients' preventive healthcare.***

***Keywords: Automated Detection, Diabetic Retinopathy, Early Diagnosis, Deep Learning, Retinal Fundus Images, Xception Architecture.***

## I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood sugar levels caused by either inadequate insulin synthesis or inappropriate insulin use. It is today one of the most common health issues in India, affecting more than 62 million people. Diabetic retinopathy (DR) is one of the most prevalent and dangerous consequences of long-term or untreated diabetes. Damage to the retina's small blood vessels causes DR, which, if left untreated, can lead to vision impairment or even irreversible blindness. Since 552 million people worldwide are expected to have diabetes by 2030, early identification and in order to avoid blindness, DR treatment has become essential [1] [2] Nevertheless, conventional image processing methods for DR diagnosis are frequently difficult, time-consuming, and necessitate professional interpretation. Deep learning techniques are already powerful instruments for medical image analysis in recent years, allowing for automated and extremely precise illness detection. In order to detect and assess the Using retinal fundus images to assess the severity of diabetic retinopathy, this study offers a deep neural network-based technique that combines CNN-based classification with U-Net segmentation for accurate region identification. The suggested strategy improves detection accuracy, lowers manual labor, and offers an affordable option for widespread diabetic retinopathy screening by integrating various techniques.


Fig 1.1 Stages of Diabetic Retinopathy

## II. OBJECTIVE

Developing a deep learning-based model for the automatic identification and categorization of diabetic retinopathy (DR) from retinal fundus pictures is the aim of this project. By determining the existence and severity of DR, the system seeks to facilitate early identification by providing a quick, affordable, and non-invasive screening method [3]. It improves the effectiveness of diagnosis and facilitates prompt treatment to avoid vision loss with a goal accuracy above 92%. The need for automated DR detection increases as diabetes rates continue to rise worldwide. The Automatic Detection of Diabetic Retinopathy (ADDR) [4] system developed for this research offers a dependable computer-based method for evaluating retinal pictures in order to automatically identify DR.

## III. RELATED WORK

One of the main worldwide health issues, diabetic retinopathy is the subject of much research due to its early detection and prevention of vision damage. Numerous studies have looked into a number of methods using deep learning and machine learning to increase diagnostic and classification accuracy. A number of research on the detection and prediction of diabetic retinopathy are examined in this section. Using APTOS dataset, Ritesh Chandra et al [1]. presented a CNN and AlexNet-based model for the diagnosis of diabetic retinopathy. The model's weak explainability, lack of generalization across datasets, and limited model comparison all hindered its ability to classify DR severity. CNN outperforms conventional techniques in feature extraction and classification, according to the study.

Using patient health information such age, blood pressure, and length of diabetes, Nor Tasha Nadira Nor Azamen et al [5]. created a machine learning based DR prediction model. The models Logistic Regression, KNN, and SVM achieved a maximum accuracy of 83.78%, although their overall generality and robustness were hampered by a short sample, retrospective data, and missing information. A CNN-based method for categorizing DR phases that made use of picture pre-processing methods including erosion and histogram equalization was introduced by Kavya Duvvuri et al [4]. A tiny dataset, a narrow scope for pre-processing, and a comparatively straightforward CNN structure in comparison to more sophisticated architectures like ResNet [5]and Inception were among the restrictions, despite the fact that this enhanced model performance.

Using the APTOS 2019 dataset, Abini M.A. and S. Sridevi Sathya Priya [7]classified retinal pictures into five DR stages using pretrained deep neural networks, namely VGG-16 and MobileNetV2. Even though the model produced encouraging findings, its generalizability was limited by dataset variability, the challenge of identifying moderate DR phases, and the lack of interpretability in model decisions. Using data augmentation methods like rotation and shearing to increase dataset heterogeneity, Samiya Majid Baba and Indu Bala created a CNN-based framework for DR detection. Although the suggested model outperformed conventional methods in terms of accuracy, it was constrained by a small dataset, class imbalance, high processing demands, and a lack of external validation.

For the identification of diabetic retinopathy, Kazi Ahnaf Alavee et al. suggested a deep learning based method that combined CNN with explainable AI models. The study used a number of pretrained models, such as DenseNet121, Xception, ResNet50, VGG16, and InceptionV3. Their suggested CNN model had the best accuracy of 95.27%. Grad-CAM visualization was incorporated to enhance interpretability, allowing increased confidence in Model predictions and clinical insights.

Katsuhiko Ogasawara and Hongjian Zhang concentrated on putting Grad-CAM-based explainable AI for text processing in medicine. With an F1-score of 90.2%, the study used Word2Vec and BERT for word embeddings and ResNet [2]and 1D CNN for classification. In order to improve medical AI models' interpretability and dependability for practitioners, the study highlighted the significance of visualization in XAI. Using hybrid feature extraction, an explainable deep neural network (xDNN) classifier for diabetic retinopathy detection and data augmentation was presented by Oualid Mecili et al. The model achieved up to 99.7% accuracy and 99.8% AUC on the MESSIDOR-2, APTOS 2019, and IDRID datasets. For practical clinical use, the study emphasized the need to strike a compromise between explainability and model accuracy.

In order to automatically diagnose diabetic retinopathy, Mahesh Gour et al. created a hybrid model called XCapsNet that combines Xception and Capsule Networks. The model obtained accuracies of 98.91% and 98.33% on the APTOS2019 and Messidor datasets, respectively, using CLAHE preprocessing for improved image contrast. In both binary and multiclass classification tasks, the results showed better performance than traditional CNNstructures. Using Kaggle datasets [8], Villeneve de O. Soares et al. investigated the Xception architecture for retinal picture classification across various phases of diabetic retinopathy. The binary classification method had a maximum sensitivity of 88.54% and accuracy of 89.74% demonstrating Xception's potential for multi-stage, unsupervised DR classification, despite its limitations due to small class overlaps.

Abdul Qadir et al. shown the applicability of such hybrid architectures to additional medical imaging domains by proposing a reliable BiLSTM-based deep learning model for the early detection and classification of knee osteoarthritis (KOA). The model demonstrated the effectiveness of combining CNN feature extraction with BiLSTM [8] sequence modeling, achieving testing accuracy of 84.09% using the Mendeley VI and OAI datasets.

## IV. PROPOSED METHODOLOGY

The suggested technique automatically identifies diabetic retinopathy from retinal fundus photos using the Xception deep learning model. The model is trained to identify characteristics that indicate the existence and severity of the illness using a labeled dataset. Resizing and normalization are two image preparation techniques that improve accuracy and quality. Xception offers quicker and more effective classification by utilizing transfer learning. This method provides a quick, non-invasive, and affordable screening option that is especially helpful in places with low resources.

### DATA SOURCE:

It used the Diabetic Retinopathy Detection 2015 and APTOS 2019 Blindness Detection datasets that were obtained from Kaggle. Thousands of images of the retinal fundus captured in various settings are included in both collections. Every topic include pictures of the left and right eyes. The photos contain a lot of noise because they are gathered from multiple sources, including different models and cameras, necessitating a number of preprocessing procedures to improve quality. On a scale of 0 to 4, each image is labeled according to the degree of diabetic retinopathy:

0 = No DR,
1 = Mild,
2 = Moderate,
3 = Severe,
4 = Proliferative.

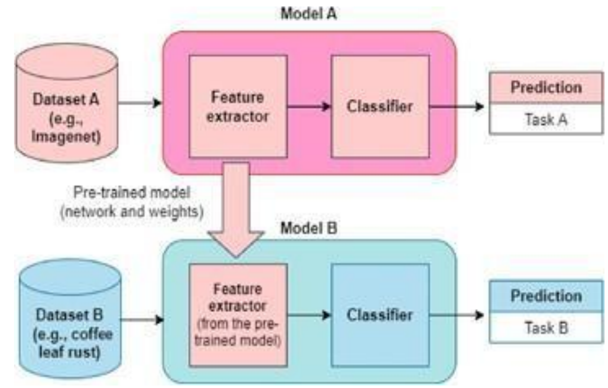


Fig.4.1 Block Diagram

### DATA PREPROCESSING:

The retinal fundus images from the dataset were preprocessed in order to standardize them for model training. because they had a number of quality problems, including uneven illumination, poor focus, excessive exposure, and noise. Preprocessing was done with the intention of improving image quality, correcting brightness differences, and eliminating unnecessary areas. During preprocessing, the following actions were taken:

• Green Channel Extraction: While the red and blue channels of RGB pictures contain more noise, the green channel offers the best contrast between blood vessels and the retinal background. As a result, only the green channel was utilized for additional processing.

• Cropping the Image: Since the pupil region is most impacted by diabetic retinopathy and provides important diagnostic features, the photos were cropped to focus on this area.

• Grayscale Conversion: To lower computational complexity and better highlight blood vessels, the cropped image was converted to grayscale.

• Binary Conversion: To make it simpler to identify anomalies, the grayscale image was transformed into a binary format that separated the bright (healthy) and dark (defected) areas of the retina.

• Noise Reduction: To improve contrast and eliminate background noise, methods including Gaussian blurring and normalization were used.

Feature Extraction and Classification:

Based on their size, shape, and color intensity, microaneurysms, hemorrhages, and exudates were identified using the Xception model. Based on their incidence and spread, these characteristics were subsequently categorized into five stages of diabetic retinopathy: Normal, Mild, Moderate, Severe, and Proliferative.

Algorithm Implementation:

To count anomalies, the processed photos were examined pixel by pixel. The neural network classifier was fed the pixel count, mean, and standard deviation values. These characteristics were used to train the model to correctly classify retinal pictures into the appropriate DR phases. By ensuring that the images were clear, consistent, and appropriate for deep learning, this preprocessing and classification pipeline improved the Xception model's ability to detect diabetic retinopathy.

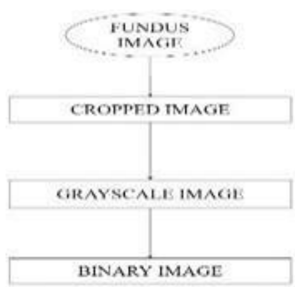


Fig.4.2 Pre-Processing Stage (PPS)

TESTING:

We tested each module in our project to make sure it fulfilled the necessary functionality and operated as intended. Finding and fixing any system flaws before to final deployment was the primary goal of testing. Various testing techniques were employed, including system, functional, integration, and unit testing. Unit testing confirmed that every single system module generated reliable results. The seamless operation of all integrated elements was guaranteed via integration testing. Functional testing verified that each system feature operated in accordance with the specifications. System testing confirmed the project's overall performance. Black box testing was used to test human interactions, while white box testing was used to test internal logic. Verifying data input, page navigation, and reaction speed were the main objectives of the test strategy. Every test scenario was completed successfully, and no significant flaws were discovered. All things considered, the testing verified that our solution operates precisely, satisfies customer needs, and guarantees a dependable user experience.

| INPUTS | POSITIVE TESTCASE | NEGATIVE TESTCASE |
|---|---|---|
| FUNDUS IMAGES | SHOWS THE RANGE OF DIABETIC RETINOPATHY | INVALID INPUT |
| OTHER IMAGES | INVALID INPUT PREFER TO RELOAD ANY OTHER IMAGES | SHOWS THE PREDICTION RANGE TO ALL IMAGES |

## V. RESULT

Using a pooled dataset from Diabetic Retinopathy Detection 2015 and APTOS 2019 Blindness Detection, which are both accessible on Kaggle, we trained our suggested model using the Xception architecture. Preprocessing was crucial because the raw photographs had a lot of noise because of differences in illumination, camera quality, and focus. In order to concentrate just on the retinal region, the black borders and corners were eliminated during preprocessing, and all images were uniformly scaled to 256 by 256 pixels [8]. Next, a Gaussian blur was used to reduce noise and improve the clarity of the image. Following preprocessing, we found that the dataset was extremely uneven, with most samples falling into the "No DR" class (class 0). Data augmentation techniques were used to address this problem, producing roughly 7000 photos per class and balancing the dataset across all severity levels. The Xception-based model was then trained using the preprocessed and enhanced photos. Following evaluation, the model showed significant generalization during validation and attained a training accuracy of 97%. The findings demonstrate that the suggested Xception model is a dependable tool for early diagnosis and clinical support since it successfully detects and classifies diabetic retinopathy with high accuracy.

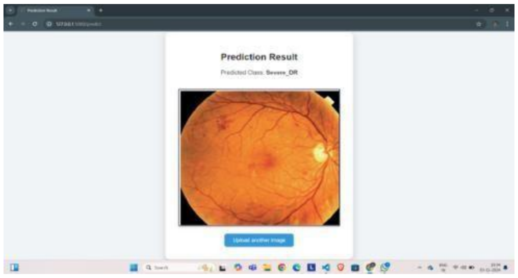


Fig. 5.1 Output

Figure 5.1. The picture displays a retinal fundus image categorized as Severe_DR on the prediction result screen of the diabetic retinopathy detection system. Additionally, it offers the ability to upload an additional image for additional prediction.

| Classes | Precision | Recall | F1-Score |
|---|---|---|---|
| 0 | 0.99 | 0.98 | 0.98 |
| 1 | 0.78 | 0.95 | 0.86 |
| 2 | 0.97 | 0.92 | 0.94 |
| 3 | 0.92 | 0.98 | 0.95 |
| 4 | 0.99 | 0.98 | 0.98 |

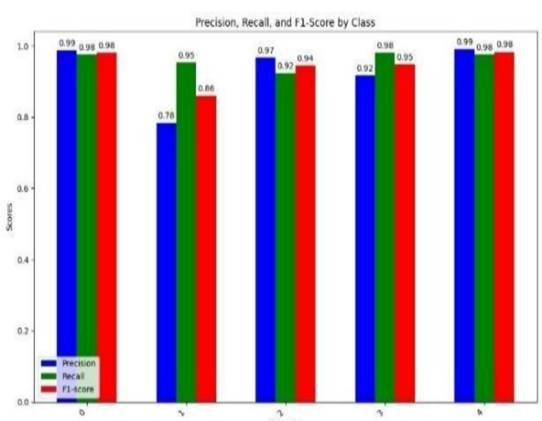


Fig. 5.2 Accuracy Chart

## VI. CONCLUSION

Using the Xception deep learning model, the suggested approach effectively identifies and categorizes Diabetic Retinopathy from retinal fundus images. Through the use of efficient preprocessing and data augmentation methods, the model attained a high accuracy of 97%, indicating its effectiveness and dependability. This technology helps with timely treatment and prevention of vision loss by offering a quick, non-invasive, and economical way for early diagnosis. The findings show that deep learning can be extremely helpful in automating medical image processing, helping ophthalmologists make clinical decisions, and enhancing patient outcomes.

## VII. FUTURE SCOPE

To improve accuracy and generalization, the suggested system might be trained on bigger and more varied datasets. Predictions can be improved by incorporating extra clinical data, such as medical records and patient histories. Additionally, real-time diabetic retinopathy screening can be made possible by creating a web-based or mobile application, particularly in rural locations. To further enhance detection performance and resilience, future studies may concentrate on integrating the Xception model with other cutting-edge deep learning architectures.

## APPENDIX

Additional experimental details and extended performance results are provided to support the main findings of this study. The appendix includes confusion matrices for each diabetic retinopathy severity class, along with model accuracy and loss graphs obtained during training. All supplementary datasets, preprocessing scripts, and trained model weights used in this work are available upon request for academic and research purposes.

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REFERENCES


[1] E. A. R CHANDRA, "CNN AND ALEXNET-BASED MODEL FOR DIABETIC RETINOPATHY DETECTION USING THE APTOS DATASET," *JOURNAL OF MEDICAL IMAGING AND HEALTH INFORMATICS,* 2021.

[2] "www.medicalnewstoday.com/articles/32362,"in *MEDICAL NEWS TODAY*, 2025.

[3] M. CLINIC, "SYMPTOMS AND CAUSES OF DIABETIC RETINOPATHY," in *www.mayoclinic.org/diseases-conditions/diabetic-retinopathy*, 2025.

[4] "DIABETIC RETINOPATHY DETECTION DATASET," in *www.kaggle.com*, 2025.

[5] "TENSORFLOW DOCUMENTATION," in *www.tensorflow.org*, 2025.

[6] "SCIKIT-LEARN DOCUMENTATION," in *www.scikit-learn.org*, 2025.

[7] "HARVAD HEALTH PUBLISHING RETINOPATHY," in *www.health.harvard. edu/a_to_z/retinopathy-a- to-z*, 2025.

[8] "THE MOST INTUITIVE AND EASIEST GUIDE FOR CONVOLUTION NEURAL NETWORK," in *towardsdatascience.com*, 2025.

[9] e. L. N.T.N.N AZAMEN, "MACHINE LEARNIG BASED DR PREDICTION USING PATIENT HEALTH DATA," in *BIOMEDICAL SIGNAL PROCESSING AND CONTROL*, 2020.

[10] K. DUVVURI, "CNN-BASED APPROACH WITH IMAGE PRE-PROCESSING FOR DR STAGE CLASSIFICATION," in *PROCEDIA COMPUTER SCIENCE*, 2021.

[11] A. A. S. PRIYA, "CLASSIFICATION OF DIABETIC RETINOPATHY USING PRETRAINED DEEP NEURAL NETWORKS VGG-16 AND MOBILENETV2," 2022.

[12] S. B. A. I. BALA, "CNN-BASED FRAMEWORK FOR DIABETIC RETINOPATHY DETECTION USING DATA AUGMENTATION," *INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS,* 2021.

[13] K. ALAVEE, "DEEP LEARNING AND EXPLAINABLE AI FOR DIABETIC RETINOPATHY DETECTION USING CNN AND GRAD-CAM," in *COMPUTER IN BIOLOGY AND MEDICINE*, 2021.

[14] H. Z. A. K. OGASAWARA, "GRAD-CAM-BASED EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR MEDICAL TEST PROCESSING," in *APPLIED SCIENCE*, 2023.

[15] O.MECILI, "EXPLAINABLE DEEP NEURAL NETWORK (XDNN) CLASSIFIER FOR DIABETIC RETINOPATHY DETECTION," in *ARTIFICIAL INTELLIGENCE IN MEDICINE*, 2023.

[16] M. GOUR, "HYBRID XCAPSNET MODEL COMBINING XCEPTION AND CAPSULE NETWORKS FOR DR DETECTION," in *BIOMEDICAL SIGNAL PROCESSING AND CONTROL*, 2021.

[17] V. SOARES, "XCEPTION ARCHITECTURE FOR RETINAL IMAGE CLASSIFICATION ACROSS DR STAGES," in *PROCEDIA COMPUTER SCIENCE*, 2022.

[18] A. QADIR, "BILSTM-BASED DEEP LEARNING MODEL FOR EARLY MEDICAL IMAGE DISEASE DETECTION," in *IEEE ACCESS*, 2023.