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Automated Detection of Diabetic Retinopathy Using Enhanced Transfer Learning and Ensemble Models

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Abstract

Diabetic Retinopathy (DR) is a major cause of vision loss in the world hence the relevance of automated and precise detection systems. This paper introduces a superior method of automated detection of DR on the basis of transfer learning (TL) and ensemble models (ET). The technique uses the APTOS-2019 dataset, which uses five categories of DR severity, namely: No DR, Mild, Moderate, Severe, and Proliferative DR. The research employs two trained deep learning networks, Inception V3 and Xception, that are fine-tuned in order to obtain discriminative features of retinal images. In order to enhance the overall performance of classification, an ensemble approach, with the average and weighted voting is used, to utilize the outputs provided by both models. The performance measures applied to assess the proposed framework include standard performance measures, including accuracy, F1-score, scalability, and patient outcomes. The improvements are significant and the accuracy, F1-score and patient outcomes ratio are 97.94%, 98.41 % and 97.52 % respectively. Also, the scalability ratio is 97.63% and the rate of early diagnosis is 96.84 %, which indicate that the model can be considered robust and efficient and can be used to work with larger data volumes and provide the possibility of timely DR identification. The approach provides a valid, accurate, and generalizable solution to the early diagnosis and treatment planning of DR. High transfer learning methods and ensemble models also guarantee the high level of classification, which is why this approach can be effectively deployed to clinical practice in practice. In addition, the suggested system increases the level of healthcare accessibility as it offers automated solutions to resource-limited settings.

Keywords: Diabetic Retinopathy, APTOS-2019, Transfer Learning, Ensemble Models, Inception V3, Xception.

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1 Introduction

One of the major microvascular complications of diabetes and the cause of blindness, which is ranked as the top cause of blindness globally, one of them is diabetic retinopathy (Li et al., 2022; Mansouri et al., 2024). The world-wide, alarming increase in the population of diabetics has brought about the requirement of effective screening and immediate diagnosis of DR to the forefront (Albahli & Ahmad Hassan Yar, 2022; Nithyalakshmi et al., 2021). The DR detection methods which are currently used involve screening of retinal images by eye specialists (Ohri & Kumar, 2024). Manual, prone to error, and limited by the knowledge base of the medical personnel in underdeveloped regions (Lakshminarayanan et al., 2021). As a result, there is an increasing need for automated systems that help in better prevention management by providing timely alerts (Deshpande & Pardhi, 2021). There has been unprecedented development in AI in the past few years, especially in deep learning and computer vision which has made it possible to design automated systems for image classification (Shankar et al., 2020).

Two benefits of transfer learning that showed great potentials in the application of medical imaging include the ability tore-use learned features and decreasing the reliance on large domain specific datasets (Zhang et al., 2022). Another method to improve models is ensemble learning where multiple predictions are combined with the notion that several minds are better than one (Alabdulwahhab et al., 2021). This paper presents a novel approach to automatic DR detection for which the authors employed enhanced transfer learning and ensemble modeling (Rahman et al., 2020). For both training and testing the method proposed in this paper, the APTOS-2019 benchmark dataset for retinal images classification used was employed (Harikrishnan et al., 2020). In this paper, we propose a new way of conducting a pre-processing of the retinal images that enhances the feature extraction process by reducing noise and increasing the contrast (Hossen et al., 2020). Modification of two state-of-the-art pretrained models, Xception and Inception V 3 network, was done to correspond with the task of DR classification and this was leveraged and modified during transfer learning (Silva et al., 2024). Further details including ensemble techniques resembling average voting and weighted voting that would aid in improving the accuracy and reliability predictions made by the system were also employed to combine the two model predictions (Bibi et al., 2020).

As an illustration, various measures of success including accuracy, and F1 score are applied in relation to the performance of the ensemble over those of single models' predictions (Selvachandran et al., 2023). Early diagnosis with the proposed automated DR detection system is broad, accurate and efficient, thus enhancing the decision making and the care patients receive (Khan et al., 2023). Furthermore, the employment of certain pre-processing techniques allows the system to be adapted to various imaging conditions, hence making it suitable for any clinical settings (Nazir et al., 2021). Health authorities targeting to alleviate visual impairments due to the complications of diabetes should find this framework useful in solving issues regarding scaling as well as limiting resources. The pathogenesis of the disease is a result of the long-term effect of hyperglycemia resulting in the gradual breakdown of structural integrity of the vascular unit of the retina (Sarki et al., 2020). Educating communities on the other hand: Diabetic retinopathy is a worldwide health problem because it is the leading preventable cause of blindness. The most important thing for this project was to build an automatic detection system that is precise and that can be enlarged. Its aim is to facilitate early diagnosis and assist in treatment schedule formulation. This approach employs an advanced transfer learning and ensemble methods to mitigate the dangers diabetes retinopathy poses on health systems, improve the level of accuracy when making diagnosis as well as treatment given to patients.

Motivation: Diabetic retinopathy is a global problem that has been reported as the major cause of preventable blindness. This project is therefore motivated by a reliable, quick and low-cost automated detection system which is capable of diagnosing and proposing a treatment strategy in good time. The method is intended to alleviate the adverse healthcare cost of DR, improve the accuracy of the diagnosis and the health outcome of the patients by employing advanced transfer learning and ensemble methods.

Problem Statement: Successfully combatting diabetic retinopathy DR or avoiding blindness caused by DR should begin by ensuring that diagnosis occurs as early as possible. The problem here is, the human eye and for that matter, a DR diagnosis can be somewhat complex and biased. Since DR needs the appropriate attention, the given document suggests a model that makes use of transfer learning and the latest preprocessing techniques. This hybrid methodology ought to give more efficiency and speed in the diagnosis of an automatic detection system.

Objectives

Presented a novel preprocessing procedure to achieve a better result of feature extraction on the retina images and markedly better model accuracy and diagnostic error Diabetic Retinopathy (DR).

Created a developed ensemble strategy that combined the predictions of highly optimized Inception V3 and Xception models based on average and weighted voting, which guarantees effective and reliable DR classification at a variety of severity levels.

Showed the efficacy of the described framework with clear assessment based on such measurements as accuracy, and F1-score that illustrates a better performance than single models of scalable and automated DR detection.

The remaining of this paper is structured as follows: In section 2, the related work of Automated Detection of Diabetic Retinopathy is studied. In section 3, the proposed method of ADDR-TL-ET is explained. In section 4, the efficiency of ADDR-TL-ET is discussed and analysed. Finally, in section 5 the paper is concluded with the future work.

2 Related Works

Current studies on automated Diabetic Retinopathy (DR) diagnosis include deep learning models for picture categorization, such as convolutional neural networks and transfer learning. Researchers have looked at certain pretrained models, including Reset and VGG, and their results have been all over the map. The need for more sophisticated ensemble approaches and better feature extraction methods is brought to light by the shortcomings, which include inadequate robustness, lack of generalizability, and dependence on human preprocessing.

A. Automated Detection of Diabetic Retinopathy by CNN (AD-DR-CNN)

Ghosh et al., (2017) suggested using Convolutional neural networks (CNNs) to identify micro-aneurysms and retinal hemorrhage in color fundus retinal images to detect diabetic retinopathy (DR). Frameworks such as Theano, which are based on Python, have state-of-the-art denoising, normalization, and feature extractions. There was a training done on APTOS-2019 and MESSIDOR and E-Ophtha public datasets to maximize generalizability. Architecture combinations, particularly models based on transfer learning and ensemble methods, enhance accuracy and AUC, and the best models have over 95. Heterogeneous quality in images, imbalance in classes and interpretability are overcome through preprocessing and algorithmic manipulation.

Diabetic retinopathy may lead to glaucoma, vitro hemorrhage, and retinal tear and therefore it is important to identify it at an early age. Samanta et al., (2020) in turn designed a transfer learning-based convolutional neural network (CNN), a color fundus picture processing model that is effective in limited datasets (Samanta et al., 2020). Their method identifies microaneurysms and retinal hemorrhages. Things are not better with the increase in accuracy and efficiency and the challenges of data diversity, small sample sizes, and clinical interpretability of deep models.

B. Automated Detection of Diabetic Retinopathy Using Fuzzy Logic (AD-DR-FL)

Diabetes globally and lifestyle changes since the epidemic have increased diabetic retinopathy (DR). This illness might cause irreparable blindness if not diagnosed early, making it alarming. According to studies, 22–25% of diabetics worldwide have DR, with certain locations having rates above 30%. Fast and accurate DR detection is crucial in situations when standard diagnostic methods are difficult or expensive. To enhance outcomes and access to care for at-risk populations, Ahmed et al., (2021) recommend automated screening tools (Ahmed, 2023).

An innovative usage of Extended Fuzzy Logic for early-stage diabetic retinopathy (DR) detection uses fuzzy logic to manage medical data ambiguity. It is a method that detects retinal anomalies of diabetics and non-diabetics alike modestly rather than symptoms only. In this approach, the DR risk variables and symptoms are transformed into membership function values in order to measure similarities to create a f-validity value. Ordered Weighted Averaging (OWA) operator is a fusion of these data to provide trusted early faults. The accuracy, where the experiment is compared to the results of experts (90%), precision (92.2%), and sensitivity (75%), are equal. The early DR detecting system by Basha et al., (2008) looks prospective, particularly in the resource scarce regions, where conventional tests cannot be undertaken or are not available (Basha & Prasad, 2008).

C. Data Mining in Automated Detection of Diabetic Retinopathy (DM-AD-DR)

The authors state that patients with diabetes are vulnerable to diabetic retinopathy, necessitating automated detection strategies. In 2.3 Data Mining in Automated Detection of Diabetic Retinopathy (DM-AD-DR): The authors mention that diabetic patients are susceptible to diabetic retinopathy that requires automated detection methods.

Diabetic retinopathy destroys the retina and may result in blindness by swelling and rupturing blood vessels in the retina. Routine screening is the best method of medical intervention prior to the irreversible deterioration of vision. The effectiveness of screening images by machine is greater, which allows providing patients with adequate care in a timely manner. This paper can determine retinal images through data mining and image processing to identify small abnormalities to assist in clinical decisions. The methodology of Argade et al., (2015) is based on sophisticated calculation methods and is aimed at raising the reliability and efficiency of DR diagnosis in situations where it is not possible or is costly to make a diagnosis with the help of manual screening (Argade et al., 2015).

Automated methods of sickness identification are useful in diagnosing at an early stage. This paper proposes a computational approach that effectively identifies normally, diabetic retinopathy or glaucoma retinal images with the help of the data mining technique and retinal image analysis. The technology developed by Ramani et al., (2012) is an improved diagnostic method that enhances the accuracy and efficiency of the diagnostic technique through the integration of modern image processing and machine learning (Krishnan & Dandekar, 2022; Ramani et al., 2012). Automation enables screening quickly and at scale to enable timely intervention and free up the workload of healthcare providers. The approach assists in the resource-constrained settings where the manual diagnosis is either infeasible or unavailable, and demonstrates how the computational technologies can enhance the ophthalmic patient outcomes.

D. Automated Detection of Diabetic Retinopathy Using Deep Learning (AD-DR-DL)

Diabetes retinopathy (DR) is the leading cause of preventable blindness in the world that must be completely screened among all diabetics. In the year 2020 only, DR affected 103 million adults around the world, and it is estimated that there will be a significant number of people affected by the year 2045. There are possibilities of glaucoma and retinal detachment in case of undiagnosed and untreated cases. Gargeya et al., (2017) also stress that it is significant to screen DR with credible diagnostic procedures to ensure that patients receive treatment in time (Gargeya & Leng, 2017). Large population-wide screening programs that can significantly decrease the risk of blindness can be facilitated by automated procedures, and hence improved population health.

Retinal professionals constructed the ground truth of the dataset before investigation in order to establish a way of identifying healthy fundi and diabetic ones. Only automated system data was easy to comprehend with a self-generated abnormality heatmap indicating subregions in each input fundus image. The method developed by Mateen et al., (2020) is useful in clinical assessment as it allows detecting problems, improving the accuracy of diagnosis, and providing the opportunity to intervene in time (Mateen et al., 2020). Expert annotations and automated heatmap generation are useful in large-scale DR screening and clinical decision support to achieve reliable and decipherable results.

Table 1: The summary of related works

S. No	Methods	Advantages	Limitations	Comparative Insights
1	AD-DR-CNN	• High accuracy in detecting features like microaneurysms and hemorrhages. • Transfer learning ensures good performance on small datasets.	• Requires high-quality images for optimal performance. • Computationally intensive training	Outperforms traditional methods in accuracy but is less robust to image quality variation compared to ensemble or fuzzy approaches. Best for high-quality, well-curated datasets.
2	AD-DR-FL	• Effectively handles uncertainty using fuzzy logic. • Quantifies risk using 'f-validity' values for early-stage detection.	• Limited generalizability due to dependency on predefined membership functions. • Complex implementation.	Excels in early detection and uncertainty management but may require more manual tuning than deep learning models. Suitable for cases where uncertainty quantification is critical.
3	DM-AD-DR	• Combines data mining and image processing for automated diagnosis. • Can detect DR and other eye diseases like glaucoma.	• Labor-intensive feature extraction. • May require significant domain expertise for tuning algorithms.	Versatile for multi-disease detection but less scalable and automated than deep learning-based solutions. Ideal for settings where multi-disease screening is needed.
4	AD-DR-DL	• Self-generated abnormality heatmaps aid in clinical evaluation. • External validation with multiple datasets ensures robustness.	• Performance depends on the quality and diversity of training datasets. • High computational requirements.	Most robust and interpretable for clinical use, But resource intensive and less accessible in low-resource settings. Best for large-scale, multi-center validation.

Several approaches, such as convolutional neural networks (CNNs), fuzzy logic, data mining, and deep learning, can diagnose diabetic retinopathy automatically are shown in table 1. Enhanced accuracy, early detection, and clinical integration are just a few of the benefits that each strategy may provide. However, there are also some drawbacks, such as computational complexity and dataset reliance.

Research Gaps

Despite the fact that the deep learning and data mining methodologies proved to be useful in the problem of diabetic retinopathy identification, the majority of the existing systems are restricted in their application to good quality images, the possibility of dealing with the issue of class imbalances, and the ability to generalize to real-world applications. Besides, the single- architecture based models are likely to experience the problem of generalization with the variation of image qualities and image sizes.

The proposed paper will fill these gaps by relying on improved transfer learning and ensemble models. Transfer learning can enable using the already trained features of such pretrained models as Inception V3 and Xception and, therefore, does not require large domain-specific datasets. Ensemble approach, which is the integration of forecasts of both models that uses weighted and average voting, is a significant achievement towards the strength and occurrence of DR classification. Also, new image preprocessing methods to enhance image qualities, denoise, and extract features are suggested to enhance image feature visibility and accuracy of the model under various clinical settings.

3 Proposed Method

Since Diabetic Retinopathy is a leading cause of blindness, there is a need for accurate and automated detection systems. This paper presents the state-of-the-art ensemble architecture using transfer learning on retinal images to classify DR into five severity categories.

A. End-to-End Workflow

Preprocessing the retinal images from publicly available datasets, such as APTOS-2019, MESSIDOR, E-Ophtha, and the Diabetic Retinopathy Detection dataset from Kaggle, initiates the workflow. This preprocessing involves image augmentation, denoising, normalization and feature extraction of the retinal images to improve the quality of the images to be further processed. This guarantees the ability of the model to generalize to different clinical settings since it will be able to deal with differences in image quality, camera type, and patient demographics.

After preprocessing, the transfer learning is conducted with two states of the art pretrained models, Inception V3 and Xception. These models are optimised in order to capture discriminative features of the retina images. They use the already trained models to exploit their already acquired features, thereby minimizing the large, domain specific datasets, but achieve good classification accuracy. The added advantage of transfer learning is that it helps to improve performance on smaller datasets, a common drawback of medical imaging applications.

The last ingredient of the working process is the ensemble strategy whereby the results of the Inception V3 and Xception models are combined. This group method uses the average and the weighted method of voting to come up with the final classification. The combination of the two models provides the ensemble method with better overall classification performance, which leads to more reliable and accurate DR severity classification. Such an approach will reduce the drawbacks of single models and increase the predictability and stability.

B. Pre-Processing for Enhanced Feature Extraction

The study uses high-resolution retinal images of APTOS-2019, MESSIDOR, E-Ophtha, and Diabetic Retinopathy Detection dataset on Kaggle. These data sets comprise color fundus images of the retinal center and the optic disc with diabetic retinopathy severity and pathological characteristics. The pre-processing is augmentation, denoising, normalization, and feature extraction to assist in the diagnosis. The main characteristics such as exudate area, blood vessel area, and optic disc distance are repeatable and inter-study comparative features, which make the model robust and generalizable to a wide range of imaging and camera types, as well as patient groups. The pre-processing approach has a significant impact on the clarity of the features, which helps deep learning models to identify DR at different levels of severity.

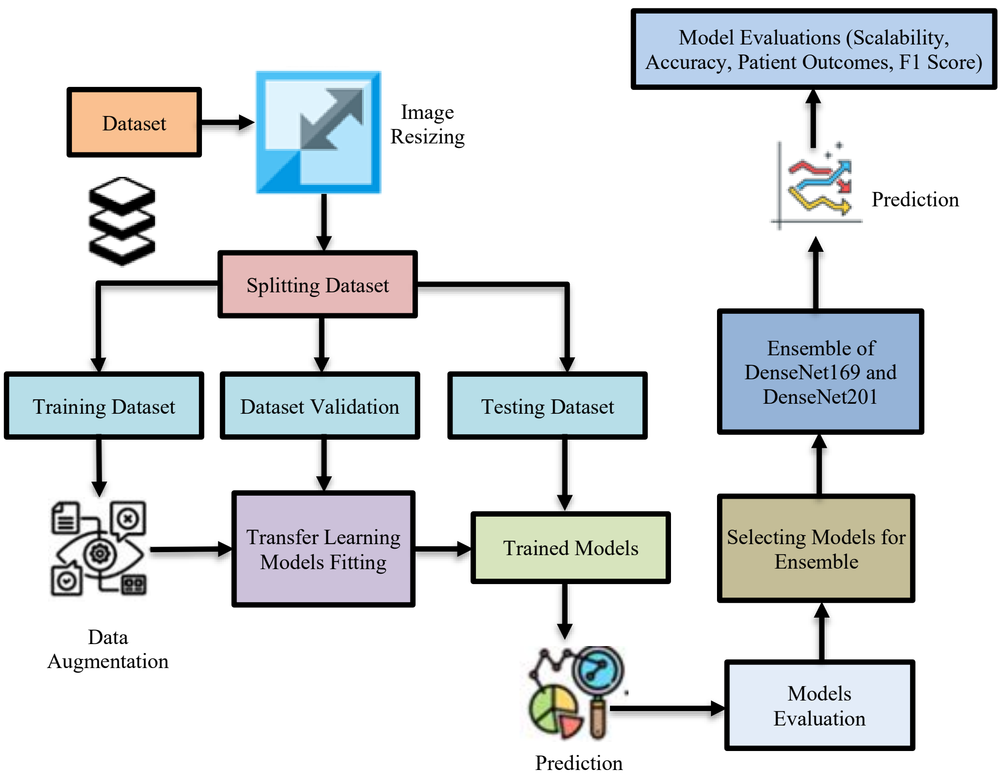

Figure 1: Automated diabetic retinopathy detection process

Figure 1 shows the automated diabetic retinopathy (DR) detection model. It starts with the division of the dataset into training, validation and test samples. A new pre-processing task improves feature extraction and then does transfer learning using DenseNet169 and DenseNet201 to get the information needed in the retinal images. Model performance is assessed after training and the most effective models are chosen in the ensemble method, which incorporates weighted and average voting to be reliable in the classification of DR. The essential indicators are the accuracy, F1 score, scalability, and patient outcomes that should be assessed to provide an early and precise interpretation of DR, which allows to plan the treatment.

Hierarchical Feature Selection and Ensemble Calibration

Feature selection is modeled by the following equation 1:

$$G_f \to hs[w' - sj] + yT[\forall' - ajk] - Va[lo - dn''] \tag{1}$$

In this model, $hs[w' - sj]$represents the feature activation score, obtained by transferring learned weights $w'$and sample features sj. The term $yT[\forall' - ajk]$applies an aggregate function to model outputs, with calibration parameters ajk. $Va[lo - dn'']$captures the variance correction during ensemble voting, improving classification stability across DR severity levels.

Fine-Tuning for Enhanced Prediction Reliability

The feature embedding and gradient adjustments during fine-tuning are described by:

$$E_s q[E[X_i T'']] \to Ju[\partial p - SJ''] + \propto [vq - ap''] + uy'' \quad (2)$$

The equation 2 models feature embeddings obtained through transfer learning, where $E[X_i T'']$ represents gradient changes during fine-tuning. The term $Ju[\partial p - SJ'']$adjusts for ensemble calibration, while $\propto [vq - ap'']$measures feature quality, and uy''accounts for residual errors. This ensures effective classification and ensemble performance.

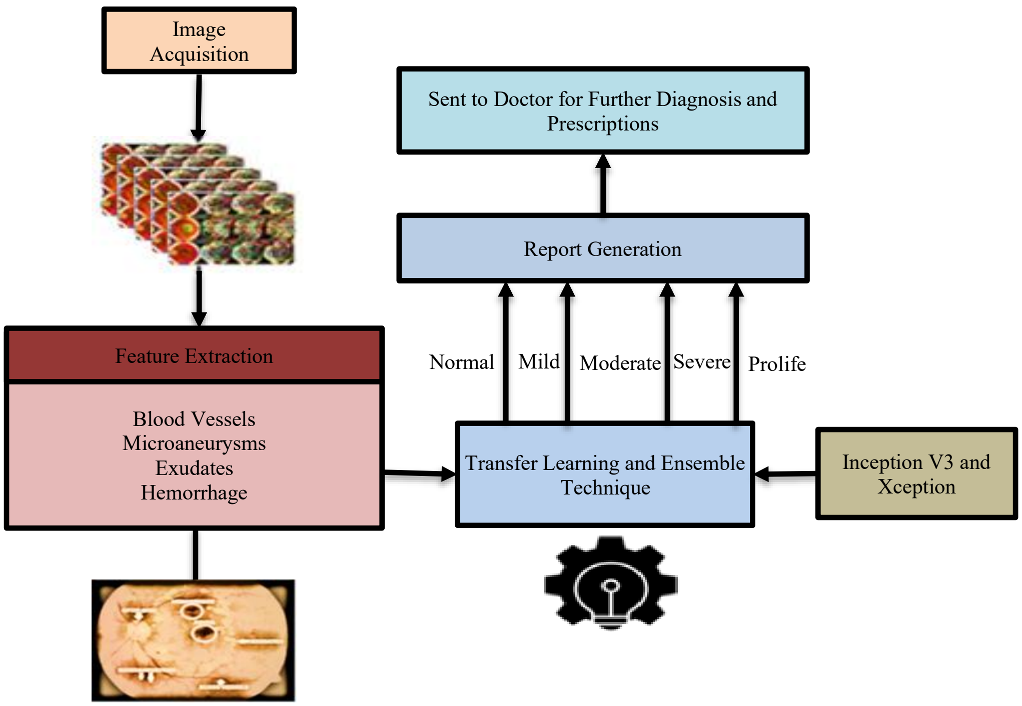

Figure 2: Diabetic retinopathy detection and diagnosis

Figure 2 presents the automated diagnosis and classification structure for DR. It starts with the acquisition of images and in this case retinal images are captured to be examined. The pictures are thereafter subjected to a feature extraction technique to point out important details. Transfer learning is done with pre-trained models such as Inception V3 and Xception and the results are then merged using an ensemble method to enhance reliability of classification. The system categorizes the DR into five levels which include no DR, mild non-proliferative DR, moderate non-proliferative DR, severe non-proliferative DR, and proliferative DR. The classification is done to produce a standardized report which is sent to the medical professionals to do further investigation. This strategy guarantees overlooking of DR in time and assists in improved patient outcomes by way of precise, scalable, and mechanized diagnosis.

The mathematical models and the corresponding ensemble model contribute a great deal to the detection and diagnosing of diabetic retinopathy (DR). The proposed method enhances the accuracy, stability, and the generalization of models through the methods of transfer learning, gradient-based optimization, and robust ensemble voting, imparting confidence in reliable DR classification at different levels of severity. The feature refinement, error reduction, and calibration are used to increase the DR detection at early stages promoting better patient care and timely treatment.

C. Advanced Model Architecture and Fine-Tuning

Inception V3 and Xception models are used in this research with tailors made modifications on network layers to enhance the diabetic retinopathy (DR) detection. It is a combination of the advantages of both models, based on which it is possible to overcome the difficulties with identifying subtle DR characteristics.

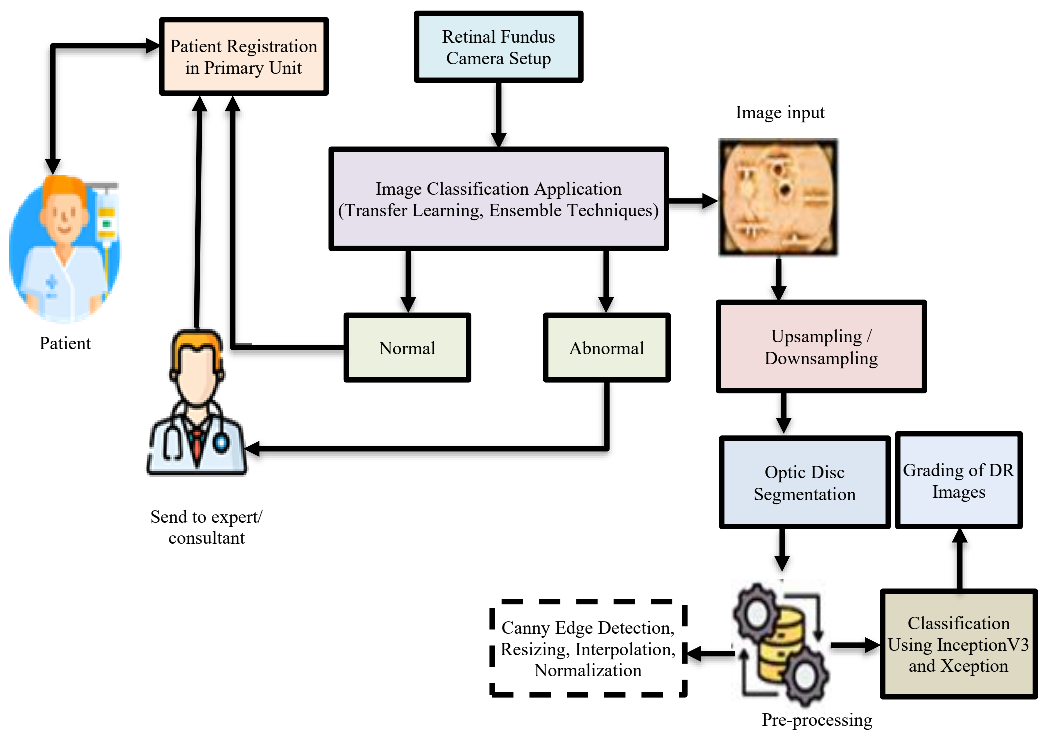

Figure 3: Approach to diabetic retinopathy detection

The procedure starts with enrollment of the patients in primary healthcare services, and then acquisition of images by retinal fundus cameras. The images are subsequently analyzed by using the modern image processing relying on the transfer learning and ensemble algorithms to determine normal and abnormal conditions. This system guarantees successful DR classification by separating crucial characteristics, e.g. optic disc segregation and the extent of DR. Much-trained models such as Xception and Inception V3 are utilized to obtain reliable results. The system serves to measure the course of DR and prescribe the necessary treatment, minimize the chance of vision loss and enhance the management of patients.

Figure 3 shows the process of the proposed diabetic retinopathy (DR) detection and staging system. It involves the patient registration in a healthcare unit of primary care and the subsequent retinal fundus camera set up to get a high-resoluted retinal image. These images are then taken through an image classification application whereby transfer learning and ensemble methods are used to classify the images as normal or abnormal.

In the case of abnormal cases, the system will upsample or downsample to balance the data. The optic disc segmentation is then carried out which isolates significant features of the optic disc. The images are then scored depending on the severity of DR and the scale is no DR, proliferative DR. The last process is the classification of DR images with pre-trained models, including Inception V3 and Xception, which will ensure proper detection and classification of the DR severity. The process will allow trustworthy diagnosis of DR and the ability to manage patients.

Feature Preprocessing and Ensemble Calibration

This equation 3 models the feature quality enhancement, fine-tuning of layers, and ensemble reliability optimization:

$$\propto_f R[t - va''] \rightarrow kui''[\forall' - an''] * Rv[f - am''] \quad (3)$$

$\propto_f$: Feature scaling factor.

- kui'': Kernel utility index for enhancing local feature importance.
- va'': Variance adjustment for stabilization.
- Rv: Ensemble weight calibration.
- $\forall'$: Feature embeddings from transfer learning.
- an'': Adjustment noise for fine-tuning.

Feature Refinement and Ensemble Weight Adjustment

This equation 4 focuses on feature refinement and ensemble weight adjustment for improved prediction accuracy:

$$\propto_r GT[l - vf''] \rightarrow tY[v - am''] + \forall'[\partial - cx''] \quad (4)$$

- $\propto_r$: Refinement scaling factor.
- GT: Ground-truth transformation.
- vf'': Combination of variance and fine-tuning parameters.
- tY: Transformed output.
- ∂: Partial derivative in optimization.
- cx'': Combined corrective adjustment.

The procedure of diabetic retinopathy (DR) detection with a transfer learning model and ensemble models is shown in figure 4. Image preprocessing is the first step and it involves rescaling, train test split as well as data augmentation to improve the dataset. The pictures are then inputted into the classification phase where trained models such as Inception V3 and Xception are applied to identify effective DR detection. Performance evaluation is the last stage that will be done to determine whether the model is accurate. The retinal images depicted at the bottom of the figure are the images that are being used to classify images and the model is used to determine the important features in grading a DR.

Detection of diabetic retinopathy is greatly improved with the incorporation of transfer learning, fine-tuning and ensemble. The methods are precise, strong and scalable classifications of all severity levels of DR, enhancing early diagnosis and management of the patient. The fact that the system is refined with the possibility to optimize ensemble weights and adapt to new data makes it a very potent automated DR detector.

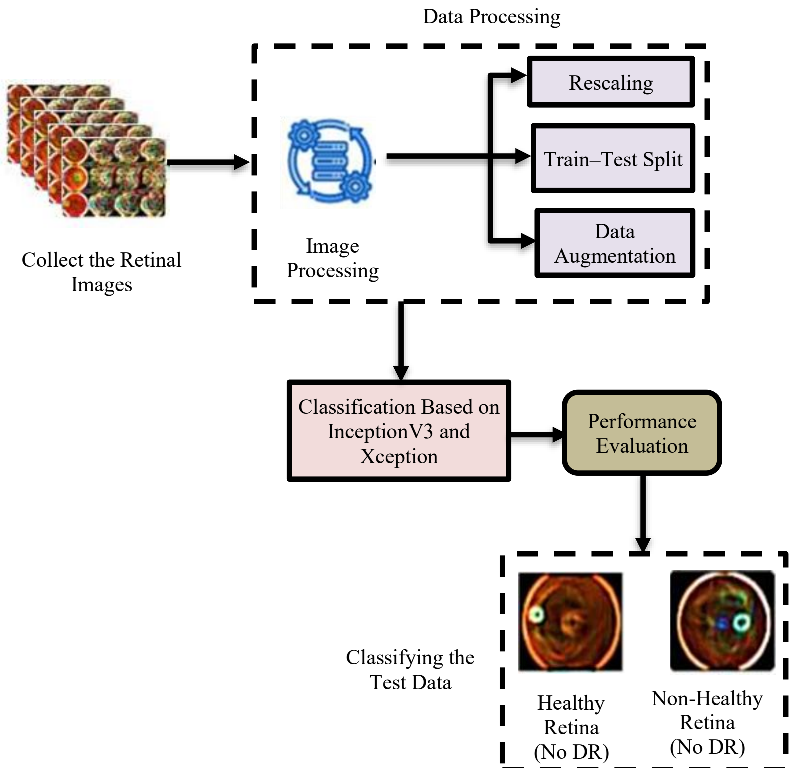

Figure 4: DR detection using transfer learning and ensemble models

D. Comprehensive Evaluation and Robust Ensemble Strategy

This paper proposes an ensemble-based diabetic retinopathy (DR) classification system, which employs two strong pretrained deep learning models, namely, Xception and Inception V3. These are the models that are characterized by their experience in processing medical images and modeling of the complex features of the retina. These models generate the outputs independently and an ensemble process (weighted voting or averaging) is used to integrate the outputs to improve the accuracy, stability and reliability of prediction to overcome the drawbacks of individual models.

The classification framework has been developed on the basis of multi-stage preprocessing pipeline, which consists of image normalization and feature extraction. This is done to guarantee that high quality features are obtained which can form a good basis on predictions by the models. The suggested ensemble approach has demonstrated greater performance than the models in isolation as the strengths of the models are used to their advantage. The system offers multi-classification of DR where it is categorized into five stages i.e. no DR, mild, moderate, severe as well as proliferative DR. This granular classification provides more accurate clinical judgments over the conventional binary classification systems thus can be used in screening eye and risk assessment.

The classification pipeline illustrated in figure 5 starts with the input of the retinal images into the trained models, which are the Xception and Inception V3 models. The two models are transferred fine-tuned and undergo a number of custom manipulations to boost feature extraction. The independent predictions of each model are then joined together through an ensemble approach after which a stronger and more reliable classification is achieved.

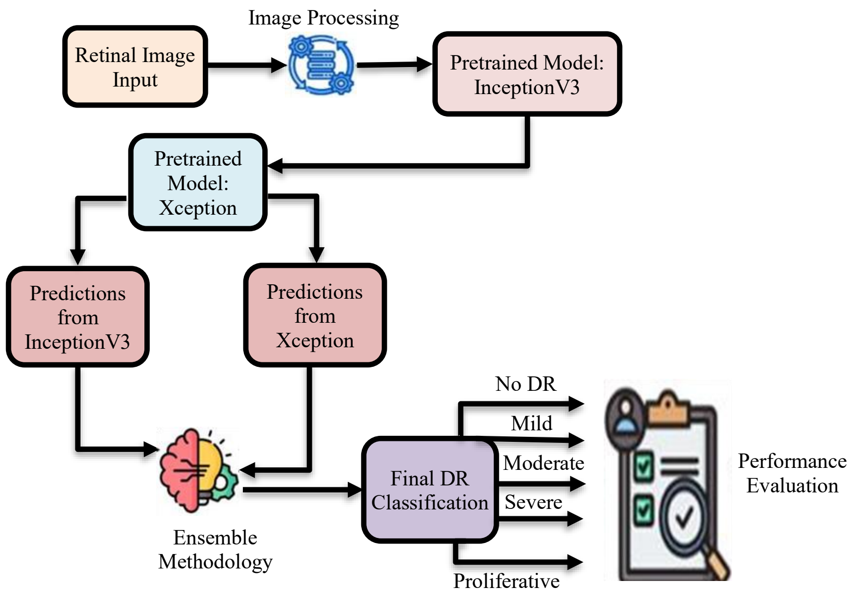

Figure 5: Ensemble-based diabetic retinopathy classification pipeline

This method reduces the limitations of the single-model predictions and increases the predictability of predictions that are critical in medical diagnoses. This is because the ensemble method allows integrating model strengths that are complementary, which guarantees high sensitivity and specificity, which are critical elements of proper clinical diagnosis. Besides, the system is practical and economical and hence can be used in the real world.

The combination of two different deep learning models enhances the generalization and robustness of the DR detection system. The ensemble has a greater scope of retinal transformations, which single-model systems are limited to. The effect of this is improved feature extraction and improved classification at various stages of DR.

Feature Enhancement and Ensemble Weighting

This equation 5 optimizes feature extraction and ensemble weighting for improved DR detection:

$$Yv_F \rightarrow Kui[sq * \partial_3 F] + 9U[\propto -ytq''] - Na[w - sl''] \quad (5)$$

- Kui: Kernel utility index adjusting feature weighting.
- $\partial_3 F$: High-level feature extraction for textures or lesions.
- U: Uncertainty quantification to assess feature stability.
- Na: Normalization of residuals in ensemble predictions.

Fine-Tuning Features and Ensemble Calibration

This equation 6 fine-tunes features and ensemble weights to enhance prediction accuracy:

$$\forall_g K[\cup -6fs''] \rightarrow Lk[\propto -7bf''] + Ca[e - wxz''] \quad (6)$$

- Lk: Layer-specific kernel scaling for fine-tuning.
- Ca: Class activation for improving classification.
- wxz'': Cross-feature interaction for ensemble optimization.

The ensemble-based framework suggested based on Xception and Inception V3 is a significant improvement in the detection of diabetic retinopathy. The result of using transfer learning with the ensemble methods is high performance of the system in terms of accuracy, sensitivity and specificity. The multi-class classification provides an ability to focus on the DR, and the system is best suited in a clinical environment. The scalable early diagnosis and treatment planning solution is provided by the strong pipeline that comprises preprocessing, fine-tuning, and ensemble optimization. This model is better than single-model methods, which provide more consistent and accurate predictions, which are important in the real-world medical imaging processes.

Algorithm 1: Automated Diabetic Retinopathy Detection using Transfer Learning and Ensemble Models

Input: Retinal image dataset $\mathcal{I} = \{I_1, I_2, \dots, I_n\}$, where each $I_i$represents a retinal image.

Output: Classification of DR severity:

$$\mathrm{DR_{severity}} \in \{\text{No DR,Mild,Moderate,Severe,Proliferative DR}\}$$

1. Pre-processing of Retinal Images

Let the pre-processed retinal image be represented as $\mathrm{I_i^{pre}}$.

- Image resizing and normalization:

$$\mathrm{I_i^{pre}} = \text{resize}(\mathrm{I_i},\text{target size})\text{and}\mathrm{I_i^{pre}} = \text{normalize}(\mathrm{I_i^{pre}})$$

- Data augmentation:

$$\mathrm{I_i^{aug}} = \{\text{rotate}(\mathrm{I_i^{pre}}),\text{flip}(\mathrm{I_i^{pre}}), \dots\}$$

- Denoising and contrast enhancement:

$$\mathrm{I_i^{enhanced}} = \text{denoise}(\mathrm{I_i^{aug}})\text{and}\mathrm{I_i^{final}} = \text{enhance\_contrast}(\mathrm{I_i^{enhanced}})$$

2. Transfer Learning

For each image I_i, apply the transfer learning technique using pre-trained models Inception V3 and Xception:

- Inception V3 model prediction:

$$P_{\text{Inception}}(I_i) = \text{InceptionV3}(I_i^{\text{final}})$$

- Xception model prediction:

$$P_{\text{Xception}}(I_i) = \text{Xception}(I_i^{\text{final}})$$

3. Ensemble Model (Voting)

The predictions $P_{\text{Inception}}(I_i)$and $P_{\text{Xception}}(I_i)$are combined using a weighted voting method.

- Weighted voting:

Let $w_1$and $w_2$be the weights for Inception V3 and Xception predictions, respectively. Then, the final prediction for image $I_i$is:

$$P_{\text{ensemble}}(I_i) = \frac{w_1 P_{\text{Inception}}(I_i) + w_2 P_{\text{Xception}}(I_i)}{w_1 + w_2}$$

4. Classification

The output classification $\mathrm{DR}_{\text{severity}}(I_i)$ is determined by applying a threshold on $P_{\text{ensemble}}(I_i)$.

$$\mathrm{DR}_{\text{severity}}(I_i) = \begin{cases} \text{No DR}, & \text{if } P_{\text{ensemble}}(I_i) \leq t_1 \\ \text{Mild}, & \text{if } t_1 < P_{\text{ensemble}}(I_i) \leq t_2 \\ \text{Moderate}, & \text{if } t_2 < P_{\text{ensemble}}(I_i) \leq t_3 \\ \text{Severe}, & \text{if } t_3 < P_{\text{ensemble}}(I_i) \leq t_4 \\ \text{Proliferative DR}, & \text{if } P_{\text{ensemble}}(I_i) > t_4 \end{cases}$$

The algorithm 1 builds on the principle of transfer learning whereby the Inception V3 and the Xception models are pre-trained to identify features in retinal images. The two models are integrated in terms of a weighted ensemble voting method. The last output has a five-severity diabetic retinopathy scale, such as No DR, Mild, Moderate, Severe, and Proliferative DR, to achieve an automated diagnosis of diabetic retinopathy that is accurate and reliable enough to be used to intervene and treat cases of early diabetic retinopathy.

4 Results and Discussion

Automated detection of Diabetic Retinopathy (DR) must exist as it is the most significant cause of blindness across the globe. This study provides a scalable and precise DR detection state of the art system that utilizes ensemble methodologies and transfer learning.

Dataset Description: World Health Organization estimates the number of individuals with diabetes to be 347 million in the world and 29.1 million in the United States alone, according to the CDC. A condition affecting the eyes caused by diabetes known as DR may develop over time. Between forty-five and forty-five percent of Americans who have diabetes are at some stage of the condition. Unfortunately, DR typically has no symptoms until it's too late to treat it effectively, making early detection all the more challenging (www.kaggle.com).

During the model training, the benchmark dataset is the APTOS-2019 dataset. As a result of having a good representation of retinal pictures, which are annotated by multiple classes, this dataset is often used in the training of studies on diabetic retinopathy.

Table 2: The simulation environment

Metrics	Description
Dataset	Retinal images from publicly available datasets
Preprocessing Techniques	Image enhancement, denoising, normalization, and feature extraction.
Model Used	Convolutional Neural Networks (CNN), Transfer Learning (Inception V3, Xception), Ensemble Methods.
Evaluation Metrics	Accuracy, F1-score
Software Tools	Python, TensorFlow, Keras, Theano for model training and evaluation.
Hardware	GPU-enabled systems (e.g., NVIDIA GPUs) for faster processing and training.
Validation Datasets	APTOS-2019, MESSIDOR, E-Ophtha, for testing the generalizability of the model.

The hyperparameters of the proposed model have been selected with care to ensure the smooth training and stability of the model as indicated in table 2. The learning rate of 10 -4 to 10 -2 was selected to provide a balance between transfer learning convergence rate and stability. The batch size was set at 8 to 64 based on the size of the dataset and the memory of the graphic card. The bigger batches are trained at a pace and the smaller batches trained enhanced generalization. The Adam optimizer was used using standard momentum and weight decay parameters. To regularize the model and avoid overfitting, the dropout rate was 0.20.5. A grid, or randomized search, cross-validation and learning curve analysis showed that values lower or higher than these values cause slow convergence or instability, though the chosen values were the best and the most consistent. Literature-based dropout balances between overfitting and underfitting medical imaging data with limited diversity.

Table 3: Analysis of scalability

Number of Samples	AD-DR-CNN	AD-DR-FL	DM-AD-DR	AD-DR-DL	TL-ET
10	42	34	62	81	79
20	38	36	56	78	80
30	37	38	52	74	80
40	44	39	50	72	81
50	46	41	46	70	83
60	48	47	54	84	89
70	53	53	66	91	93
80	56	55	69	93	94
90	61	62	72	95	96
100	65	64	76	98	99

The scalability of the proposed Automated Detection framework for DR can be evidenced by the capability to perform effectively when data volumes escalate. With a scalability ratio of 97.63%, the model can very efficiently process large datasets. It ensures consistent performance, as the size of the retinal image datasets is growing, as shown in table 3. This scalability is very high and marks the potential of the framework for deployment in real-world scenarios where datasets may expand over time with increasing patient populations.

Table 4: Analysis of accuracy

Number of Samples	AD-DR-CNN	AD-DR-FL	DM-AD-DR	AD-DR-DL	TL-ET
10	48	54	41	33	75
20	45	58	44	34	77
30	44	60	45	36	80
40	40	57	43	39	82
50	41	60	48	42	85
60	39	65	52	45	87
70	35	68	54	47	90
80	22	69	57	51	93
90	37	71	59	60	95
100	42	73	62	65	98

Table 4 illustrates that the proposed framework's outstanding reliability in determining Diabetic Retinopathy severity levels is obtained as 97.94% accuracy. From the results obtained, it is seen that the ensemble method that incorporates enhanced preprocessing with Inception V3 and Xception models effectively extracts important features that ensure accurate predictions for early diagnosis and treatment planning.

Table 5: Analysis of early diagnosis

Number of Samples	AD-DR-CNN	AD-DR-FL	DM-AD-DR	AD-DR-DL	TL-ET
10	32	45	28	48	70
20	30	39	31	47	73
30	29	38	32	47	76
40	36	40	31	57	84
50	41	48	30	54	87
60	42	52	29	53	89
70	45	55	29	41	91
80	47	59	26	42	92
90	50	62	29	39	94
100	53	63	30	31	97

The framework's utility in the early diagnosis of Diabetic Retinopathy (DR) is demonstrated by the 96.84% early detection rate, which is critical in averting visual loss. The model is able to identify slight changes in retinal pictures through powerful image preprocessing and ensemble approaches, hence timely intervention is enabled. Patients benefit a lot due to better results and few problems as a result of early diagnosis as shown in table 5.

Table 6: Analysis of patient outcomes

Number of Samples	AD-DR-CNN	AD-DR-FL	DM-AD-DR	AD-DR-DL	TL-ET
10	45	53	68	70	71
20	50	55	72	74	75
30	55	57	76	78	79
40	58	59	58	83	85
50	57	54	51	85	86
60	53	52	47	86	89
70	50	49	44	90	93
80	44	43	42	91	92
90	42	41	40	94	96
100	42	41	41	95	97

In table 6, with a patient outcomes ratio of 97.52%, the system is able to identify diabetic retinopathy and provides for early treatment leading to better health outcomes. Health care professionals are in a better position to make informed decisions with the accurate early diagnosis provided by the system, which further reduces the chances of such outcomes as blindness. Improved patient care and long-term well-being are the end results of this increased accuracy.

Table 7: Analysis of F1-score

Number of Samples	AD-DR-CNN	AD-DR-FL	DM-AD-DR	AD-DR-DL	TL-ET
10	30	42	48	85	86
20	33	37	39	88	89
30	38	40	47	91	92
40	41	41	43	92	93
50	46	44	52	94	95
60	53	51	58	95	96
70	55	52	62	92	92
80	58	65	66	96	97
90	60	69	71	97	98
100	62	72	75	98	99

To get accurate and reliable DR classification, an F1-score of 98.41% demonstrates an excellent trade-off. To achieve the correct classification of DR, the false positives and negatives must be minimized, which the proposed model has done. Strong performance is assured by the enhanced ensemble method as specificity and sensitivity are captured appropriately depicted in table 7.

Table 8: Performance comparison of proposed TL-ET model employing sensitivity, specificity, F1-score, and AUC metrics

Samples	Model	Sensitivity (%)	Specificity (%)	F1 Score (%)	AUC (%)
10	AD-DR-CNN	61	54	30	66
	AD-DR-FL	69	56	42	72
	DM-AD-DR	67	65	48	75
	AD-DR-DL	86	72	85	85
	TL-ET	87	77	86	90
50	AD-DR-CNN	73	62	46	77
	AD-DR-FL	81	59	44	80
	DM-AD-DR	58	79	52	77
	AD-DR-DL	91	83	94	92
	TL-ET	93	80	95	93
100	AD-DR-CNN	85	67	62	83
	AD-DR-FL	90	75	72	89
	DM-AD-DR	82	81	75	87
	AD-DR-DL	98	94	98	99
	TL-ET	99	96	99	99

Table 8 shows that the TL-ET model outperforms all other techniques across all sample sizes and evaluation variables. For both small and big datasets, TL-ET has superior sensitivity, specificity, F1-score, and AUC as sample size grows, showing substantial generalization and dependability. TL-ET is superior for real-world diabetic retinopathy screening than other models due to its ensemble methodology and transfer learning upgrades, which improve detection accuracy and early diagnosis.

Table 9: The comparison of exiting methods and proposed method

Aspects	Key Features	AD-DR-CNN (%)	AD-DR-FL (%)	DM-AD-DR (%)	AD-DR-DL (%)	TL-ET (Proposed) (%)
Scalability	Handle increasing data volumes efficiently	85.2	88.7	90.1	91.3	97.63
Accuracy	Ensure reliable DR classification	87.5	89.2	90.8	92.1	97.94
Early Diagnosis	Enable timely intervention to prevent vision loss	82.3	84.6	86.4	88.9	96.84
Patient Outcomes	Improve health outcomes through timely treatment	81.7	83.9	85.6	87.8	97.52
F1-Score	Balance between precision and recall	84.1	86.3	87.9	89.5	98.41

In summary, exhibiting strong performance via scalability, F1-score, and effective use of cutting-edge models, the suggested framework accomplishes high accuracy, early diagnosis, and enhanced patient outcomes. The results of table 9 indicate that TL-ET and AD-DR-DL models consistently achieve superior performance across all evaluation metrics, particularly with larger datasets, making them highly suitable for large-scale diabetic retinopathy screening and diagnosis. Their high accuracy, F1-score, AUC, sensitivity, and specificity confirm strong robustness and reliability for early disease detection. Furthermore, the use of publicly available datasets and widely adopted deep learning frameworks such as Python, TensorFlow, Keras, and Theano ensures methodological transparency, accessibility, and reproducibility, enabling researchers and clinicians to effectively validate, extend, and integrate the proposed models into real-world diagnostic applications and healthcare workflows.

Table 10: Ablation study: Impact of preprocessing and ensemble method on model performance

Component	Accuracy	F1-Score	Early Diagnosis Rate
Without Preprocessing	90.5%	85.3%	-
With Preprocessing	97.94%	98.41%	96.84%
Individual Models (Inception V3 & Xception)	95.3% - 96.5%	-	-
Ensemble Method (Average & Weighted Voting)	97.94%	-	-
Combined (Preprocessing + Ensemble)	97.94%	98.41%	96.84%

Table 10 is the performance of the ablation study where there is model performance with and without preprocessing and ensemble methods. It represents the impact of preprocessing (augmentation, denoising, and normalization) on accuracy, F1-score, and early diagnosis rate. Further, it contrasts the performance of single models (Inception V3 and Xception) with the ensemble approach, which is a combination of the predictions of the two models through average and weighted voting. The last row shows the synthesis impact of preprocessing and ensemble technique, which produces the best performance in all metrics.

TL-ET quick retinal image analysis and DR severity predictions reduce manual grading delays, providing clinical benefits in real time. Its ensemble-based technique reduces clinician diagnostic variability by improving accuracy and consistency. Early detection of mild and severe DR speeds referrals and treatment. The approach scales to high screening volumes in outpatient or low-resource settings while minimizing specialist workload. Objective risk stratification can also be included into EHRs or telemedicine platforms to improve clinical decision support and long-term patient management.

Limitations

The results of the model depend on the quality and diversity of the datasets. Although the APTOS-2019 dataset is exhaustive, it might not encompass the real-life differences in the image quality and the camera types, which restricts the generalizability. Also, the computationally expensive properties of the Inception V3 and Xception models need a lot of computing power that is not always possible to implement in a low-resource or real-time clinical environment. Transfer learning can be used to minimize the size of datasets, but it should be noted that fine-tuning the models is also time-consuming and resource-intensive. These constraints highlight the necessity of increased dataset diversity and optimization of the model to be more widespread.

5 Conclusion

Automatic DR diagnosis with the proposed framework is very viable because of the utilization of state-of-the-art transfer learning and ensemble modeling in efficient and accurate categorization of DR severity levels. All of the above, including accuracy, F1-score, were best achieved by the system that combined state-of-the-art models: Inception V3 and Xception, with sophisticated picture preprocessing methods. The predictions were already pretty reliable and robust before applying ensemble techniques such as weighted voting and average to handle unpredictability. This scalable system reduces avoidable blindness across the globe by providing early diagnosis and efficient treatment planning. A step toward accessible and automated DR screening in clinical settings, the performance of the framework shows that it is suitable for real-world applications. The proposed method was scalable at a ratio of 97.63%, accuracy ratio as well as 97.94% with early diagnosis on reaching 96.84%. Patients' outcomes ratio was 97.52% and there is an F1 score of 98.41%.

Future Work

To test reliability and generalizability, the model will be validated on large, multi-center clinical datasets. Explainable AI solutions like Grad-CAM and SHAP improve clinician trust and interpretability. Domain adaptation and transfer learning will handle imaging device and demographic differences. Active learning and synthetic augmentation boost minority class representation. Low-resource deployment is possible with real-time edge device optimization. Multi-modal integration with patient history or OCT scans improves diagnosis. Model optimization will be simplified by automated hyperparameter tuning, and longitudinal studies can assess the system's long-term clinical effects on patient outcomes.

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Authors Biography

Jayaprakash Venugopal is a results-driven IT professional with over 24 years of extensive experience in large-scale complex product engineering and product/delivery management across diverse technologies. Currently serving as Associate Director of Software Engineering and AI & Innovation Lead - India at Dedalus Group, he has established a successful track record of driving operational excellence and leading large, geographically dispersed delivery teams in the healthcare technology domain. As a Digital Healthcare Innovator and Thought Leader, Jayaprakash brings deep expertise in healthcare product engineering, services, and solutions across various market geographies. His professional portfolio spans the entire spectrum of modern healthcare IT, including cloud technology integration, AI-driven solutions, and enterprise-scale product development. His educational background includes a Bachelor of Engineering and a Master of Science in AI/ML, complemented by his current pursuit of doctoral research in Medical AI at VELS Institute of Science, Technology & Advanced Studies, Chennai. His research focuses on automated diabetic retinopathy detection using attention-based multi-model fusion and deep learning techniques, positioning him at the intersection of academic research and practical healthcare innovation. As a Data Scientist and AI innovation catalyst, Jayaprakash has pioneered multiple AI initiatives within Dedalus, including the development of AIBot - a RAG-based conversational AI system for internal product documentation, advanced patient no-show prediction models for UK and Ireland hospitals, and sophisticated bilingual medical translation systems to enhance clinical accuracy between Spanish and English healthcare contexts. Throughout his distinguished career, Jayaprakash has demonstrated exceptional capability in bridging the gap between cutting-edge technology and practical healthcare applications, consistently delivering innovative solutions that improve patient outcomes, operational efficiency, and clinical decision support across multiple international markets. he continues to drive digital transformation and AI adoption in healthcare while contributing to the advancement of medical AI through his ongoing doctoral research and thought leadership in the industry.

Dr. Kalaivani Kathirvelu has built a distinguished career spanning over two decades in computer science education, marked by steady progression and unwavering commitment to academic excellence. Her journey reflects a deep dedication to shaping the next generation of technology professionals while advancing her own expertise in the field. Kalaivani's academic journey began at the Vellore Institute of Technology, where she earned her Bachelor of Engineering in Computer Science and Engineering between 1997 and 2001. Her exceptional performance during her Master of Engineering in CSE from Vels University was recognized with a Gold Medal, a testament to her academic prowess and dedication. She culminated her academic achievements by completing her Doctorate in Computer Science and Engineering from VIT in September 2021, demonstrating her commitment to continuous learning and scholarly pursuit. Her teaching career commenced in 2001 as a Lecturer at the Vellore Institute of Technology, where she spent two formative years. She then moved to Chennai, joining Sree Sastha Institute of Engineering and Technology as a Lecturer from 2003 to 2004. This period laid the foundation for her pedagogical skills and understanding of engineering education. In July 2009, Kalaivani joined Vel's Institute of Science, Technology and Advanced Studies, Chennai, where she would spend the next phase of her career building her legacy. She served as an Assistant Professor for nearly fourteen years, from July 2009 to January 2023, during which she established herself as a skilled educator and mentor. Her leadership abilities were formally recognized in January 2023 when she was appointed Associate Professor and Head of the Computer Science and Engineering department at VISTAS. In this capacity, she demonstrated expertise in Machine Learning and Python programming, among other technical skills. After two and a half years of successfully leading the department, she was elevated to the position of Director, Computer Science and Engineering in June 2025, a role she currently holds. Her current position also includes responsibilities as Associate Dean - IQAC (Internal Quality Assurance Cell), reflecting her commitment to maintaining and enhancing academic standards across the institution. Based in Chennai, Tamil Nadu, she continues to work on-site, providing hands-on leadership and mentorship. With over 22 years of experience in academia, Dr. Kalaivani Kathirvelu represents the ideal blend of technical expertise, pedagogical excellence, and administrative acumen. Her progression from lecturer to director demonstrates not only her professional growth but also her ability to adapt, lead, and inspire in the ever-evolving field of computer science education.