CLASSIFICATION OF DIABETIC RETINOPATHY IMAGES USING MOBILENETV2

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ABSTRACT

Diabetic Retinopathy (DR) is a condition in which lesions develop on the retina due to type-2 diabetes, leading to vision impairment if not detected early. Traditional methods for DR detection rely on manual examination and conventional computer vision techniques, which depend on accurate feature extraction of complex retinal structures. In recent years, Deep Learning (DL) methods, particularly Convolutional Neural Networks (CNNs), have gained significant importance for image classification and DR detection. However, conventional CNN models using standard convolution operations often result in high computational complexity and large memory requirements. To address these limitations, the proposed work introduces a MobileNetV2-based CNN classifier that utilizes depth-wise separable convolutions for efficient feature extraction, thereby reducing computational cost and memory usage. The approach leverages pretrained weights to improve feature learning and for classification performance use XGBoost. The model employs the Adam optimizer along with a cross-entropy loss function to enhance convergence and minimize loss during training. Experimental results demonstrate that the proposed model achieves an overall accuracy of 98%, with a precision of 94.67%, sensitivity of 94.68%, specificity of 98.67%, and F1-score of 94.65%. These results indicate that the model provides efficient and reliable performance for multi-class DR classification. Thus, the proposed approach enhances deep learning–based detection capabilities for complex medical imaging problems and contributes to the advancement of automated diabetic retinopathy diagnosis.

Keywords: Diabetic Retinopathy, Deep Learning, MobileNetV2, Convolution Neural Networks, Retinal image classification

INTRODUCTION:

DR is an eye condition associated with diabetes. It is due to damage to the retina's neurons and tiny blood vessels. Diabetics lead to the formation of aberrant new blood vessels in the retina, it can cause blood vessels to enlarge and leak, obstructing blood flow[9]. Diabetic Retinopathy is characterized by certain symptoms such as spots or black threads in vision, distorted or fluctuating vision, decreased colour vision, dark or empty areas in vision, and vision loss. There are two types of DR:1. Non-Profilerative DR(NPDR) 2.Proliferative DR(PDR).Fig:1 represents the Typical NPDR image and a Typical PDR image.

A small blood vessel leak that causes the retina to enlarge is considered an NPDR. The primary cause of vision loss in diabetes people is macular edema, a condition in which the macula swells, another factor that affects vision loss is Macular - ischemia which results in the closure of blood vessels within the retina This leads to the stoppage of blood that reaches to the macula that leads to the formation of tiny particles called exudates. PDR is the most advanced form of diabetic retinopathy that develops when untreated. That causes the growth of new blood vessels in the retina to occur abnormally. When newly formed blood vessels obstruct fluid flow, creating pressure within the eyeball. Additionally, blood seeps into the vitreous, a jelly-like substance found in the middle of the eye. The aforementioned elements cause damage to the optic nerve leading to vision loss[10].

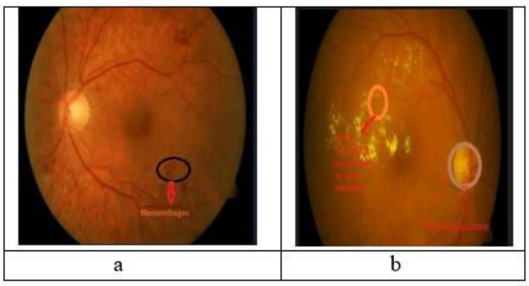

FIGURE 1:(a) Typical NPDR (b) Typical PDR

Globally, about 420 million individuals have been identified as having diabetes mellitus. This disease has become common in the last 30 years24, and more cases are predicted, especially in Asia. Diabetic retinopathy (DR), a chronic eye disease that can lead to irreversible vision loss, is predicted to affect about one-third of people with diabetes [11].

The methods that can treat DR include vitrectomy, scatter laser treatment, and focal laser treatment. Surgery is not a treatment for diabetic retinopathy; rather, it frequently slows down or stops the condition from developing. Future retinal injury and vision loss are also possible because it is a lifelong condition. Therefore, a correct diagnosis of the illness is essential. diagnostic techniques such as fluorescein angiography and optical coherence tomography, which require applying an external substance or dye to the patient's eye following the acquisition of a retinal image. However, a more comfortable and practical approach for physicians and patients alike is an Automated System that can detect DR with immediate accuracy without the need for any external agent. For this CNN technique is developed CNN has already been used to make accurate predictions in several industries, including intelligent automation and healthcare. In this work, its strength is utilized to effectively diagnose diabetic retinopathy from eye pictures, with CNN accurately classifying the condition based on severity. Without the need for user input, this system will automatically identify DR[12].

By Knowing its capabilities, CNN is used in this proposed work for the Classification of stages of DR. Allocating images to thematic classes automatically is the aim of image categorization. Supervised and unsupervised classification are the two classification methods. The image classification process consists of two stages: training of the system and testing The method of training entails, extracting the distinct qualities from the pictures and creating a class. The purpose of the testing step is to classify the test images under the different classes that is trained for. This allocation of classes is conducted in accordance with the division of classes[13].

Objectives of the proposed work are:
1. To detect the stages of DR a CNN classifier MobileNetV2 is developed, and used a TL method for reduction of Time consuming and improve performance.
2. In this study used a preprocessing method for resizing the images to reduce the training time and machine resources.

RELATED WORK:

Over the years, significant research has been carried out in the field of diabetic retinopathy (DR) detection using deep learning techniques. The rapid advancement of convolutional neural networks (CNNs) has significantly improved image classification performance, particularly in medical image analysis. These models are capable of automatically extracting complex features from retinal fundus images, thereby enabling accurate and efficient detection of DR. Consequently, several researchers have proposed various deep learning-based methodologies incorporating preprocessing, feature extraction, transfer learning, and attention mechanisms to enhance the classification performance and reliability of DR detection systems.

A. J. Kadhim et al. [1] proposed a hybrid deep learning framework for multiclass diabetic retinopathy classification by combining color-based blood vessel segmentation with CLAHE Top-Hat feature extraction. These preprocessing techniques enhance retinal structures and improve lesion visibility in fundus images. The extracted features are fused and classified using pretrained VGG19 and InceptionV3 models with transfer learning. Additionally, data augmentation is applied to address class imbalance in the Kaggle DR dataset. The method classifies images into five severity levels, where the VGG19 model achieved superior performance with 96.7% accuracy, 97.1% sensitivity, and 98.1% specificity..

C. Huang et al. [2] proposed a hybrid deep learning and optimization-based model for accurate early-stage DR detection. The framework integrates MobileNet-V2 as an efficient feature extractor with an Improved Fire Hawk Optimizer (IFHO) for optimal feature selection and hyperparameter tuning. Preprocessing techniques such as Wang–Mendel noise reduction and SMOTE are incorporated to improve data quality and handle class imbalance. Experimental results demonstrated high diagnostic performance with 96.98% accuracy and 98.54% recall, indicating the effectiveness of combining deep learning with optimization algorithms..

K. A. Alavee et al. [3] presented an integrated deep learning framework combining multiple transfer learning models along with explainable artificial intelligence (XAI) for diabetic retinopathy detection. The study evaluates pretrained models such as DenseNet121, Xception, ResNet50, VGG16, VGG19, and InceptionV3 for both binary and multiclass classification. A customized CNN model is also developed to improve performance, which outperformed other models and achieved an accuracy of 95.27% on the APTOS dataset.

A. Jabbar et al. [4] proposed a lesion-based hybrid deep learning framework for diabetic retinopathy detection and severity classification using retinal fundus images. The model utilizes transfer learning architectures such as GoogleNet and ResNet-16 for feature extraction. Additionally, an Adaptive Particle Swarm Optimizer (APSO) is applied to enhance feature representation. The extracted features are classified using machine learning algorithms including Support Vector Machine (SVM), Random Forest, and Decision Tree, resulting in improved classification performance.

W. L. Alyoubi et al. [5] presented a comprehensive review on deep learning–based techniques for diabetic retinopathy detection using retinal fundus images. The study highlights the importance of early detection to prevent vision loss and discusses the limitations of manual diagnosis. The authors emphasize that convolutional neural networks (CNNs) are the most effective models for automated DR analysis and review several state-of-the-art approaches used in clinical applications.

Y. Abushawish et al. [6] presented a survey on deep learning–based automatic diabetic retinopathy detection and grading systems. The study discusses the transition from traditional machine learning methods to advanced CNN-based architectures. It highlights the role of transfer learning, hybrid models, and end-to-end learning in improving detection performance. The importance of explainable AI is also emphasized, where techniques such as Grad-CAM are used for visual interpretation of model decisions.

R. Romero-Oraa et al. [7] proposed an attention-based deep learning framework for diabetic retinopathy grading using fundus images. The model introduces a novel approach by separating dark lesions and bright lesions using image decomposition and attention mechanisms. Transfer learning with the Xception model is used for feature extraction. The method improves interpretability and classification performance, achieving 83.7% accuracy with a Quadratic Weighted Kappa score of 0.78.

Arias-Serrano et al. [8] proposed an artificial intelligence–based system for automated detection of glaucoma and diabetic retinopathy using a retrained AlexNet convolutional neural network. The model applies transfer learning and preprocessing techniques such as cropping and resizing for retinal images. It classifies images into non-disease, glaucoma, and diabetic retinopathy categories and achieved high validation accuracy, demonstrating the effectiveness of AlexNet in multi-disease detection.

Dataset :

This study used a dataset from the open source called Kaggle. This dataset consists of High-resolution fundus(HRF) images which are used for training and testing of the proposed architecture. The dataset is distinguished into 5 different Stages namely 0. No DR 1.Mild 2.Moderate DR 3. Profilerative DR(PDR).4.Severe.Fig 2 represents the images of Four Stages in Dataset. The dataset consists of [3662] images, it includes [1805] No DR images ,[370] Mild DR images

[999]Moderate DR images, [295],PDR images and [193] Severe DR images.

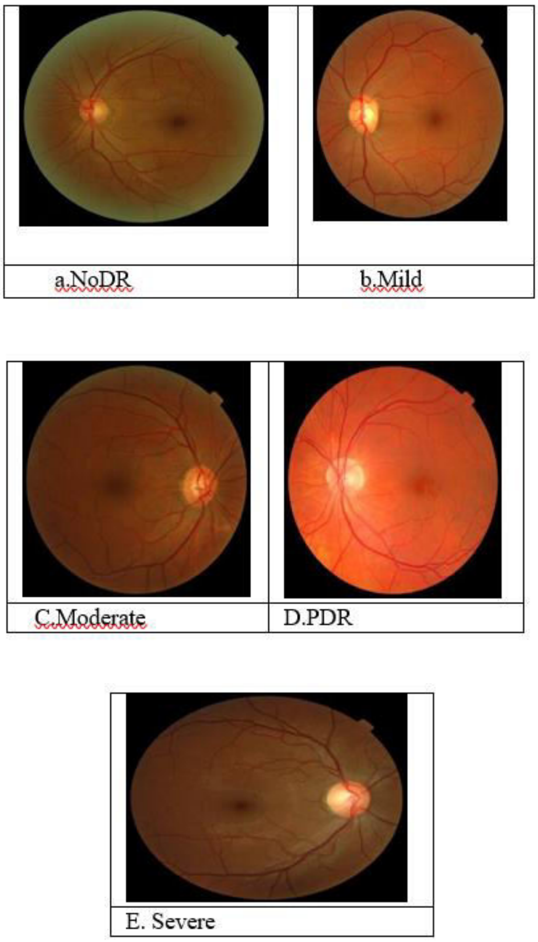

FIGURE:2 Images of Five stages in Dataset

METHODOLOGY:

Data Preprocessing

Data preprocessing is a crucial stage in the proposed system, as it enhances the quality and consistency of the input images before feature extraction and classification. In this work, the preprocessing pipeline consists of image resizing, noise removal, and data augmentation to improve model performance and generalization capability.

Initially, all input images were resized to a fixed dimension to maintain uniformity throughout the dataset. Image resizing reduces computational complexity and ensures compatibility with the deep learning model architecture. By converting images into a standard size, the model can process all samples efficiently without dimensional mismatch.

After resizing, noise removal techniques were applied to eliminate unwanted distortions such as random pixel variations, blur, or background artifacts present in the images. This step improves image clarity and enhances the visibility of important features. Filters such as Gaussian filtering can be used to smooth the images while preserving significant structural details.

Following noise reduction, data augmentation was performed to artificially increase the size and diversity of the training dataset. Various augmentation operations such as rotation, flipping, zooming, shifting, brightness adjustment, and shearing were applied to generate modified versions of existing images. This process helps prevent overfitting and enables the model to learn robust features under different orientations and conditions.

Feature Extraction:

CNNs are specifically engineered to interpret organized grid data. They comprise several layers, including fully connected, pooling, and convolutional. Due to their ability to dynamically learn hierarchical representations of characteristics straight from the data, CNNs are particularly good at object detection, image segmentation, and classification tasks. Modern computer vision applications rely heavily on them because they effectively learn and generalize complicated patterns by utilizing spatial hierarchies and parameter sharing.

MobileNetV2:

MobileNetV2 offers several benefits when used for image Classification. First of all, its thin architecture makes it possible to install it effectively on embedded and mobile devices with constrained processing power. Second, compared to more expansive and computationally costly models, MobileNetV2 achieves comparative accuracy. The model is appropriate for real-time applications since its compact size allows quicker inference times. MobileNetV2 enables tasks like image classification, object detection, and semantic segmentation on devices with limited processing power and memory, extending the reach of deep learning to mobile platforms.

Feature extraction is an important stage in the proposed system, where meaningful and discriminative information is obtained from the preprocessed images for accurate classification. In this work, **MobileNetV2** was employed as the feature extraction model due to its lightweight architecture, fast computation, and high performance in image analysis tasks.

MobileNetV2 is a deep convolutional neural network specifically designed for efficient processing with fewer parameters and lower computational cost. It utilizes **depthwise separable convolutions**, which reduce the number of operations while maintaining strong feature learning capability. In addition, it uses **inverted residual blocks** and **linear bottlenecks**, which help preserve important image information and improve network efficiency.

In the proposed method, the preprocessed images were provided as input to MobileNetV2. The final classification layer of the pretrained network was removed, and the deep intermediate layers were used to extract high-level feature representations. These extracted features contain essential patterns such as edges, textures, shapes, and structural characteristics present in the images.

The generated feature vectors were then forwarded to the next stage for classification using the **XGBoost** classifier. By using MobileNetV2 as a feature extractor, the system achieves reduced computational complexity, faster training time, and improved classification performance. Overall, MobileNetV2 provides an effective and reliable solution for extracting robust features in the proposed image classification framework.

Fig 3 represents the Flow diagram of the proposed method. In this proposed work, the input HRF images undergo the process of Resizing, which resizes the image into 244*244 pixels and that ensures that all input images have the same dimensions. Where resizing helps in the reduction of overfitting and improves Scalability. Then, using a Dataset consisting of DR images, the model is trained by initializing certain parameters like No.of epochs, learning rate, etc. Then the features are extracted using CNN layers by using certain types of filters and techniques and then stages are classified. To enhance the performance of the MobileNetV2 approach, this study uses a XGBoost method which uses a pre-trained model, and certain layers are replaced according to the required classification.

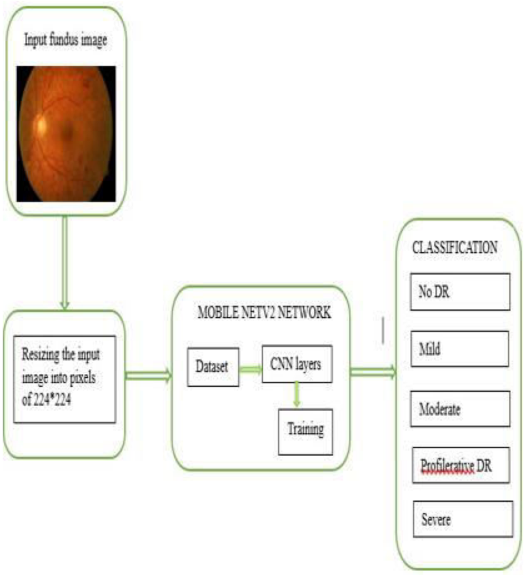

FIGURE 3: Flow diagram of the proposed method

MOBILENETV2 ARCHITECTURE

MobileNetV2 represents a significant advancement in CNN architecture, offering a compelling combination of performance, efficiency, and versatility for mobile and embedded vision applications.

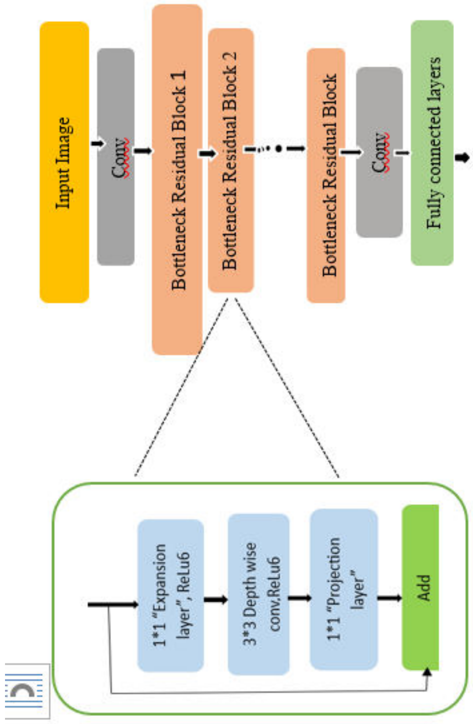

FIGURE 4: MobileNetV2 Architecture

Fig:4 represents the Architecture of MobileNetV2 that employs depthwise separable convolutions, and inverted residuals with linear bottleneck residual (BR) blocks. Each BR block consists of a 1*1 Expansion layer,3*3 Depth depth-wise convolution, and 1*1 projection layer. The input image gets convoluted and fed to the BR block where Depth-wise separable convolution happens which leads to efficient feature extraction and reduction of Computational cost and the projection layer leads to reduce the size. Then the output of the BR block is again convoluted and fed to the Fully connected layers for classification of stages of DR.

XGBoost

In the proposed system, **XGBoost** was used as the primary classification algorithm to improve prediction accuracy and model reliability. XGBoost is an advanced ensemble learning technique based on gradient boosting, where multiple decision trees are generated sequentially and each new tree minimizes the errors produced by the previous trees. This iterative learning process enables the model to capture complex patterns and nonlinear relationships present in the dataset.

The selection of XGBoost was motivated by its superior performance, computational efficiency, and robustness when compared with conventional classifiers. It incorporates regularization techniques that reduce overfitting and enhance generalization capability, making it suitable for real-world datasets. In addition, XGBoost supports parallel processing and optimized tree pruning, which decreases training time while maintaining high accuracy.

In this work, the extracted features were provided as input to the XGBoost classifier, which categorized the samples into their respective classes. The model performance was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrated that the XGBoost-based classification framework achieved reliable and efficient performance, proving its suitability for the proposed application.

EVALUATION METRICS

Performance matrices aid in evaluating many aspects of the model's performance and guiding improvements in model architecture and training methods. This proposed approach used performance matrices like Accuracy, Recall, F1 score, and precision for Evaluating the performance of the MobileNet V2 architecture[26].

EXPERIMENTAL RESULTS:

Training Analysis:

Training the model with appropriate hyperparameters plays a crucial role in improving the overall performance of the system. In the proposed approach, 75% of the dataset is utilized for training, 15% for testing, and the remaining 10% for validation to ensure proper evaluation and generalization of the model. The model is trained using the Extreme Gradient Boosting (XGBoost) algorithm, which is an efficient ensemble learning technique based on gradient boosting. The training process is guided using a multi-class logarithmic loss function (mlogloss), which is suitable for multi-class classification problems.

Figure 5 represents the training history of the model by illustrating both training loss and validation loss across boosting iterations. At the beginning of the training process, both losses start at a relatively high value (around 1.6), indicating that the model initially has limited knowledge about the dataset. As the number of iterations increases, both training and validation loss decrease rapidly, especially during the first 50–100 iterations, which demonstrates that the model is effectively learning important patterns from the data.The training loss continues to decrease steadily and eventually reaches near-zero values, showing that the model fits the training data efficiently. Simultaneously, the validation loss also decreases smoothly without any sudden fluctuations, indicating stable learning behavior and good generalization capability on unseen data. The absence of an increase in validation loss suggests that overfitting is effectively controlled. Overall, the graph confirms that the model achieves stable convergence and strong predictive performance during training.

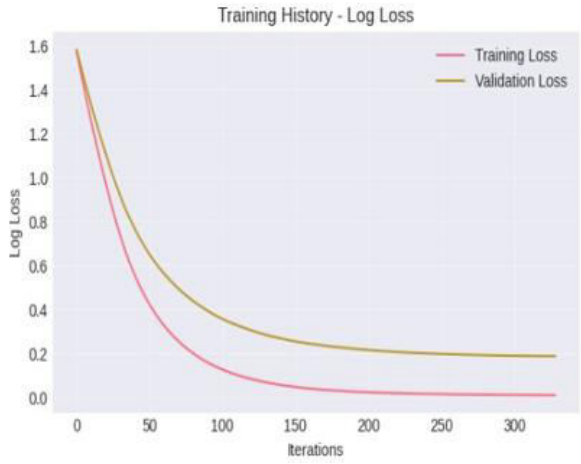

FIGURE 5: Training and Validation Log Loss over Iterations

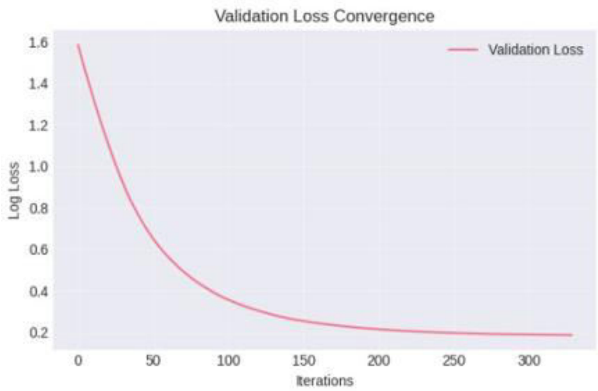

Figure 6: Validation Log Loss Convergence over Iterations

Figure 2 illustrates the convergence of validation loss during training. Initially, the validation loss starts at a high value (around 1.6) and decreases rapidly as the boosting iterations increase, indicating improved model performance. After several iterations, the validation loss stabilizes around 0.18, demonstrating smooth convergence and good generalization on unseen data. The absence of fluctuations or increases in validation loss indicates that overfitting is effectively controlled.

Confusion matrix:

A confusion matrix is a tabular representation that is used in classification tasks to assess the performance of a machine-learning model and it is a clear overview of the model's performance, allowing the calculation of several evaluation metrics such as accuracy, precision, recall, F1 score, and specificity. it is in the form of an N*N matrix. Table 2 represents the confusion matrix of the MobileNet V2 in which rows correspond to the actual classes and columns correspond to the predicted classes.. Table 3: Represents the Observations from Mobile Net V2 Confusion Matrix..

Table 1: : Confusion matrix of the MobileNetV2

		Predicted classes[percentage]				
	Input classes	No DR	Mil d	Mod erate	PD R	Sev ere
Act ual clas ses	No DR	98.15	0.37	1.48	-	-
	Mild	2.21	95.94	1.85	-	-
	Modera te	1.85	5.54	87.45	2.21	2.95
	PDR	0.74	1.48	3.07	0.37	93.70
	Severe	0.74	1.48	3.7	0.37	93,70

The table 1 represents the confusion matrix of the proposed model for diabetic retinopathy classification across five classes: No DR, Mild, Moderate, PDR, and Severe. The model achieves high classification accuracy for most classes, with 98.15% correct prediction for No DR and 95.94% for Mild DR. The Moderate class records an accuracy of 87.4%, where a few samples are misclassified as Mild, PDR, and Severe due to similarities in disease characteristics. For the advanced stages, the model achieves 93.7% accuracy for both PDR and Severe classes, indicating effective detection of severe retinal abnormalities. Overall, the confusion matrix demonstrates that the model performs robustly with minimal misclassification and strong generalization capability across all diabetic retinopathy stages.

Table 2: Observatins from MobileNet V2 Confusion Matrix

	Heal thy	Mild_ DR	Moderate _DR	PD R	Sev ere
TRUE positives(TP)	266	260	237	253	265
FALSE Negatives (TN)	5	11	34	17	5
FALSE Positives (FP)	13	21	22	9	7
TRUE Negatives (FN)	1070	1062	1061	1075	1077

The table2 represents the classification performance metrics of the proposed diabetic retinopathy detection model in terms of True Positives (TP), False Negatives (FN), False Positives (FP), and True Negatives (TN) for five classes: Healthy, Mild DR, Moderate DR, PDR, and Severe DR. The model achieves a high number of true positive predictions across all classes, with 266 correctly identified Healthy samples and 265 correctly identified Severe DR samples. Moderate DR shows comparatively higher false negatives (34), indicating that some moderate cases are misclassified due to overlapping retinal features with adjacent stages. The false positive values remain low for all categories, demonstrating that the model effectively minimizes incorrect predictions. Additionally, the large number of true negatives for every class confirms strong discriminative capability and reliable classification performance of the proposed system.

Table 3: result of MobileNetV2-XGBoost model on all the classes of DR

model	CL	LBL	ACC	PRC	RCL	F1
obileNetV2-XGBoost	No DR	0	97.73	95.34	98.15	96.73
	Mild	1	96.71	92.53	95.94	94.2
	Moderate	2	94.95	91.51	87.45	89.43
	Severe	3	98.17	97.43	98.15	97.79
	PDR	4	97.15	96.56	93.7	95.11

CL: Class; **LBL:** Label; **ACC:** % Accuracy;

RCL: % Recall; **PRC:** % Precision; **F1:** % F1- Score

The table 3 represents the performance evaluation of the proposed MobileNetV2-XGBoost model for diabetic retinopathy classification using Accuracy (ACC), Precision (PRC), Recall (RCL), and F1-score metrics across five classes. The model achieves excellent performance for the No DR class with an accuracy of 97.73% and recall of 98.15%, indicating highly reliable identification of healthy retinal images. For the Mild DR class, the model attains balanced performance with an F1-score of 94.20%, demonstrating effective early-stage disease detection.The Moderate DR class records comparatively lower recall (87.45%) and F1-score (89.43%) due to similarities between intermediate disease stages, which may lead to minor misclassifications. The Severe DR class achieves strong performance with 98.17% accuracy and 97.79% F1-score, confirming effective recognition of severe retinal abnormalities. Similarly, the PDR class attains high precision (96.56%) and F1-score (95.11%), indicating robust classification capability for proliferative diabetic retinopathy. Overall, the results demonstrate that the proposed MobileNetV2-XGBoost model provides accurate and reliable multiclass diabetic retinopathy classification across all disease stage

Table 4: Comparison of the Proposed model with other DL models.

Ref	Metho d	Acc urac y %	Sensiti vity/R ecall %	Preci sion %	F1- Score %
A.Jawad Kaghim et al.[1]	VGG and Incepti on V3	96.7	97.1	98.1	96.33
Sinthana yothin et al.[28]	K-NN	80.2	75.66	79	81
Parshva Vora et al.[29]	K-fold Cross-Validat ion	76.6	70	78.5	80
Leiyu Chen et al.[23]	VGG Net	81	79.6	80	83.2
Propose d Method	Mobile Net V2-XGBo ost	98	94.68	94.67	94.68

Table 4 represents the Comparison of the Proposed model with other DL models. The VGG and InceptionV3 have obtained the accuracy, sensitivity, precision, and F1-Score as 96.7%,97.1%,98.1%, and 96.33 respectively. They can observe the performance of other models whereas the proposed model achieved better performance i.e. accuracy, sensitivity/Recall, precision, and F1-Score as 98%,94.68%,94.67, and 94.68% respectively.

CONCLUSION:

A diabetic retinopathy classification method using the MobileNetV2-XGBoost model is proposed to demonstrate the effectiveness of deep learning techniques in automated retinal disease detection. In this approach, MobileNetV2 is utilized for efficient feature extraction, enabling the model to learn important retinal image features with reduced training time and improved performance. XGBoost is further employed as the classifier to accurately categorize diabetic retinopathy stages, including No DR, Mild, Moderate, Severe, and PDR. The model achieved strong performance across all evaluation metrics, obtaining an overall accuracy of 98%, precision of 94.67%, recall of 94.68%, and F1-score of 94.68%. The confusion matrix and class-wise performance analysis further confirm that the model effectively distinguishes different stages of diabetic retinopathy with minimal misclassification. These results demonstrate that the proposed method provides an accurate, reliable, and computationally efficient solution for multiclass diabetic retinopathy classification and can support early diagnosis and automated retinal screening systems

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