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Detection of diabetic retinopathy and classification of its stages by using convolutional neural network

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ABSTRACT

Diabetes detection is pivotal in disease management and complication prevention. Traditional screening methods, like blood tests, are invasive and time-consuming. Deep learning has emerged as a non-invasive and automated alternative for diabetes detection. Convolutional neural networks (CNNs) excel in image analysis tasks, making them ideal for this purpose. This paper employs a CNN-based method for diabetes prediction using retinal images, utilizing the DenseNet169 architecture for feature extraction and diabetic retinopathy (DR) prediction. The APTOS 2019 blindness detection dataset from Kaggle, containing around 13,000 retinal images, is used for training. Pre-processing and normalization precede feature extraction, followed by the prediction of the DR stage. The model aims to classify retinal images into five stages of DR (0 to 4), ranging from no DR to proliferative DR. Our model achieved over 82% accuracy, outperforming advanced algorithms. Model evaluation includes accuracy, precision, recall, and F1 score measures.

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1. INTRODUCTION

Diabetes mellitus is a condition where the body fails to process sugar (glucose), resulting in increased blood glucose levels called hyperglycemia [1]. This is because the body can either fail to produce enough insulin or have an ineffective response to the insulin produced. Diabetes is not curable, but manageable. However, if not controlled, it can give rise to severe complications like nerve damage, heart attack, kidney failure, and stroke. For instance, in 2017, about 10% of the world's population had diabetes, with the possibility of reaching 11% by 2045, according to [2].

Diabetes comes in two main types: type-1 (T1D) and type-2 (T2D). Type 1 usually shows up in teens and adults, causing high blood sugar, lots of thirst, and frequent trips to the bathroom. Treatment usually involves insulin. On the other hand, type 2 often hits older adults and comes with extra health issues like obesity, high blood pressure, and cholesterol problems [3], [4]. T2DM poses a global health concern, leading to increased disability levels and healthcare costs. DN (diabetic nephropathy) and diabetic retinopathy (DR), the primary complications, cause irreversible blindness and kidney diseases. Early detection aids interventions for favourable outcomes, given the similar microvascular pathophysiological factors in the eyes and kidneys [5]. Quick and accurate diabetes diagnosis is vital due to the increasing number of cases due to improved living standards. Machine learning (ML) aids initial diabetes diagnosis but relies on feature selection and suitable classifiers. An automated DR diagnostic model [6] uses convolutional neural networks (CNNs) for disease stage classification, leveraging their established success in large-scale

image recognition. CNNs capture translation-invariant features efficiently, necessitating fewer parameters compared to fully connected networks, aligning with research goals. Traditional ML models struggle with complex data, while CNNs in deep learning (DL) excel due to advanced pre-processing, convolutional functions, and adaptability with deeper networks [7], [8]. DL models offer varying capacities in feature extraction and image classification for DR diagnosis, but evaluating an all-encompassing DL model in a single test setup lacks reliability.

Convolutional networks [9] excel in large-scale image and video recognition. An innovative visualization method for elucidating intermediate feature layers and classifier operations was introduced in [10]. The accessibility of vast public image databases like ImageNet created by [11] and sophisticated computing systems such as graphics processing units (GPUs) or extensive distributed clusters developed by [12] has enabled these advancements. The evolution of deep visual recognition structures has been notably shaped by the ImageNet large-scale visual recognition challenge (ILSVRC) [13]. This contest has served as a platform to test various versions of extensive image classification systems, spanning from complex shallow feature encodings to deep ConvNets. This research opts for CNNs due to their success, comprising convolutional and fully connected layers tailored for two-dimensional (2D) input arrangements. CNNs utilize local connections and tied weights for translation-invariant features, offering easier training with fewer parameters compared to fully connected networks [14].

The main contribution of this research paper is summarized as follows, the dataset used for our DR detection model is the APTOS 2019 blindness detection [15] dataset from the Kaggle platform. Which contains approximately 13,000 images of the retina obtained by fundus photography under various imaging conditions. In the DenseNet169 architecture, a CNN model has been proposed for feature extraction and prediction of DR. Proposed techniques are also compared with existing modern methodologies such as CNN [16], extreme gradient boosting (XGBoost) [17], and deep neural network (DNN) [18].

The organization of the paper is as follows: section 1 presents the introduction, followed by section 2, which covers the literature review. Section 3 outlines the methodology, while section 4 encompasses the results and discussion with a comparative analysis, leading to the conclusion in section 5.

2. LITERATURE REVIEW

DR is a serious complication of diabetes that affects the eyes, potentially leading to vision impairment or even blindness. It's super important to detect things fast because checking them by hand isn't always accurate and can make lots of mistakes. Recognizing the critical need for an intelligent system to enhance predictive efficiency, numerous researchers and medical professionals have turned to more sophisticated techniques for extracting features and classifying images to detect early signs of DR. This has resulted in a proliferation of works employing both ML and DL techniques.

DL techniques, especially in fundus image analysis, surpass ML methods due to their efficiency in handling extensive datasets, mitigating overfitting, and improving prediction accuracy. Amechanized DR classification frame work coordinating pre-processing, include extraction, and classification stages, utilizing profound CNN and different ML procedures. Exchange learning and dimensionality decrease help highlight extraction XGBoost demonstrates superior accuracy for DR classification [17], following a comprehensive comparison of ML methods.

The authors propose an automated DR detection system using CNNs trained on Messidor and Kaggle data. 13 CNN architectures pre-trained on ImageNet via transfer learning are tested on various image qualities [19]. A comprehensive review of automated microaneurysm detection for the early diagnosis of DR is presented. The authors highlight the significance of early DR detection and the role of microaneurysms in diagnosis. Various techniques for microaneurysm detection, such as thresholding, morphological operations, machine learning, and deep learning, are overviewed. The study offers a thorough evaluation of multiple techniques for detecting early signs of DR [20]. The authors evaluated AlexNet as a suitable CNN architecture for DR detection. They performed a comparative examination using various CNN architectures-DenseNet201, NASNetMobile, InceptionV3, ResNet50, MobileNet, and MNASNet-on a dataset containing 23,513 retinal images [21]. A comparison study analyzed multiple CNN architectures (ResNet50, NASNetMobile, InceptionV3, MobileNet, DenseNet201, and MNASNet) with a dataset of 23,513 retina images [22].

An extensive assessment of 13 pre-trained CNNs was conducted, utilizing the MESSIDOR and Kaggle datasets to detect DR [23]. A method improves DNN performance on retinal optical coherence tomography (OCT) images by removing select deep convolutional layers from networks like GoogLeNet, ResNet, and DenseNet, yielding enhanced accuracy and reduced computational load [24]. A multi-branch CNN for DR screening and staging from wide-field optical coherence tomography angiography (WF-OCTA) achieved 95.6% accuracy in screening and 91.7% in staging. Their model, focusing on vessel, lesion, and texture analysis, outperforms existing methods in WF-OCTA-based DR assessment [25]. The study

introduces an ensemble of multi-stage CNNs for automated DR grading, combining pre-trained CNNs (InceptionV3, Xception) to enhance accuracy. The multistage patch-based deep CNN (MPDCNN) achieved 96.2% accuracy in fivefold cross-validation, demonstrating effectiveness in automating DR grading [26]. The study introduces an advanced automated DR screening system using a pre-trained CNN. It employs a two-stage transfer learning approach, enhancing initial layers and utilizing principal component analysis (PCA) for feature extraction. The method, with a gradient-boosting-based classification layer, outperforms existing techniques, demonstrating superior accuracy and resilience [27]. DL models' adaptability for universal DR screening was assessed in [28]. A study explored the clinical value of a deep learning algorithm (DLA) to detect referable DR in different subgroups using Inception-v3, ResNet101, and DenseNet121 architectures with both global and local datasets. Inception-v3 performed better globally, while DenseNet121 excelled locally. Model overestimation compared to ophthalmologists' diagnoses was noted, with the local dataset outperforming foreign data by 5–8% in Kappa scores [29]. The suggested DLA comprises preprocessing, feature extraction, and classification stages. Retinal fundus images were employed for training and assessing the proposed model.

A study was conducted by [30] to evaluate the performance of various SVM classifiers in distinguishing diabetic retinopathy (DR) from normal occurrences. This was achieved by utilizing different sets of characteristics with feature extraction using AlexNet and ResNet101 and feature selection based on ACS (ant colony system). An attempt to create a deep-learning model to detect DR utilizing fundus images is made in [16]. Their model for DR achieved 92.71% accuracy, 91.89% sensitivity, and 92.90% specificity, was validated at SIOVS, and was labeled as a potential DR screening tool. The proposed CNN method by [31] efficiently categorizes DR severity in retinal images but needs refinement for improved accuracy and reduced overfitting due to training-validation disparities.

DL models outperform traditional ones in DR analysis, leveraging a deeper architecture. DenseNet, contrasting with ConvNets, fosters a more connected network by sharing feature maps across layers through concatenation. Transfer learning with DenseNet from ImageNet initializes the network for improved performance on target datasets, especially those with similar visual characteristics. This enhances feature extraction, enabling models to understand nuanced details and textures within images learned from ImageNet's diverse object categories.

3. METHOD

Traditional methods for DR detection often rely on manually engineered features and rule-based systems. However, these approaches may struggle to capture the complex patterns and variations present in retinal images. Additionally, they heavily depend on the expert knowledge of ophthalmologists and might not scale well with large datasets due to their limited ability to handle diverse data. In contrast, DL methods, such as CNNs like DenseNet169, offer a more data-driven approach. They learn hierarchical representations from raw data, automatically extracting relevant features from images. This allows them to effectively capture intricate patterns and variations present in retinal images, improving their performance on complex tasks like DR detection.

The proposed methodology begins with data collection, assembling a dataset of retinal images for DR diagnosis. Once obtained, the images undergo preprocessing, which involves resizing them to a uniform size (224×224 pixels), normalizing pixel values, and potentially augmenting the data to increase its diversity. A pre-trained model like DenseNet169 serves as the foundation for transfer learning. The model architecture can be customized by adding or modifying layers as needed before compiling it with appropriate loss functions, optimizers, and evaluation metrics. The dataset undergoes division into training and validation sets. The model undergoes training using the training dataset, with parameters set for a defined number of epochs. During training, callbacks are applied for functionalities like early stopping and learning rate adjustment, and class weights are utilized to handle class imbalances. The model's performance is evaluated using the validation dataset, calculating various metrics. Fit the model to the training data while adjusting the network's weights to minimize the loss between predicted and true labels. Employing techniques like learning rate reduction and early stopping optimizes the model's performance.

In Figure 1, the flow chart of the proposed work shows the steps involved in this methodology. The image dataset of retina’s is used from APTOS 2019 blindness detection in Kaggle. They provided a huge dataset of retina images that are acquired using fundus photography and provided a severity level of 0–4 with each image by a clinician. The images are preprocessed for normalization and resizing, and one hot encoding is applied for better classification. DenseNet169 architecture, a CNN model used for feature extraction and prediction of diabetic retinopathy. DenseNet169 is a CNN design that adeptly captures image features through dense connections among its layers. Every layer receives feature maps from all previous layers, fostering a deep network with reduced parameters. This dense connectivity enables the network to capture

complex patterns and variations in retinal images, facilitating better DR detection. The growth rate, denoted as 'k', represents the incremental count of channels in each layer. This characteristic results in improved computational and memory efficiency in each compositional layer. The sequence involves pre-activation batch normalization (BN) and rectified linear unit (ReLU), followed by a 3×3 convolution, generating output feature maps enlarged by 'k' channels.

The efficiency of DenseNet highlights its ability to streamline the network by reducing the need for numerous channels. This efficiency is attributed to the growth rate parameter, 'k', which determines the additional channels received by each layer shown in Figure 2. By leveraging this architecture, DenseNet achieves improved computational and memory efficiency compared to traditional ConvNets, presenting a promising innovation in the field of neural networks.

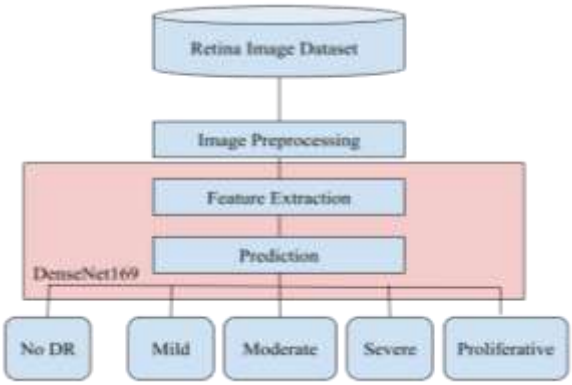


Figure 1. Flow chart of proposed work

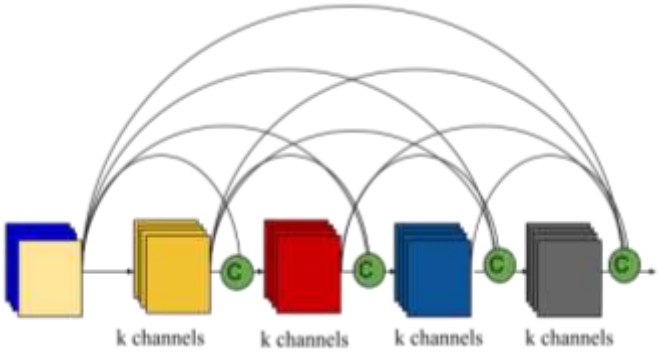


Figure 2. k Growth rate

Table 1 provided represents the distribution of DR levels among individuals, with corresponding labels and the number of individuals falling into each category. The information can be visualized through a graph to illustrate the distribution of DR levels: X-axis (labels). The different levels of DR (0 for no DR, 1 for mild, 2 for moderate, 3 for severe, and 4 for proliferative) are listed. Y-axis (number of persons): represents the count or frequency of individuals within each DR level category. The graph in Figure 3 displays bars for each level of DR, with the height of each bar representing the number of individuals falling into that particular DR level. By visualizing this data, it becomes easier to comprehend the distribution of DR severity levels among the given population.

Table 1. Number of persons in each class

Level of D	Labels	Number of persons
0	No DR	1805
1	Mild	999
2	Moderate	370
3	Severe	295
4	Proliferative	193

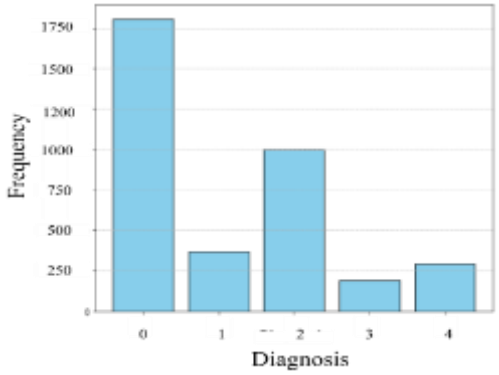


Figure 3. Distribution of classes on the y-axis are the number of persons and on the x-axis are stages of diabetic retinopathy

Table 2 summarizes the clinical features linked to different DR levels. It categorizes DR severity levels numerically and outlines corresponding observable retinal manifestations. This concise guide assists in recognizing and characterizing distinct disease stages based on clinical retinal features.

Table 2. DR levels and categories with their clinical manifestations

Level	Category	Clinical manifestation
0	No DR	Lesion-free
1	Mild DR	Microaneurysms, small hemorrhages, or mild retinal changes
2	Moderate DR	Hemorrhagic diabetic retinopathy, Venous Beading and possibly cotton wool spots
3	Severe DR	Widespread hemorrhages, cotton wool spots, and Venous Beading
4	Proliferative DR (PDR)	Neovascularization, formation of fibrous tissue, vitreous hemorrhage, or retinal detachment

4. RESULTS AND DISCUSSION

The proposed model centers around DenseNet169, trained and tested on a dataset of 13,000 fundus pictures, and targets five distinct DR classes. The images are sourced from APTOS blindness detection, Kaggle dataset, are labelled and thoroughly assessed are shown in Figure 4. With a target image measure of 224×224, it utilizes CNN preprocessing, SoftMax activation, and the Adam optimizer with a consistent learning rate of 0.01 and categorical cross-entropy as its preferred loss function throughout 50 epochs. The DenseNet169 model was initially designed with 13,070,405 parameters, out of which 12,912,005 were trainable and 158,400 were non-trainable for a 224×224 input size. To combat overfitting, a strategy of early-stopping is implemented. With this strategy, the model counters the overfitting problem and maintains a training accuracy of 84.95% and a validation accuracy of 82%. While the training loss stood at 0.5375, the validation loss was 0.51069.

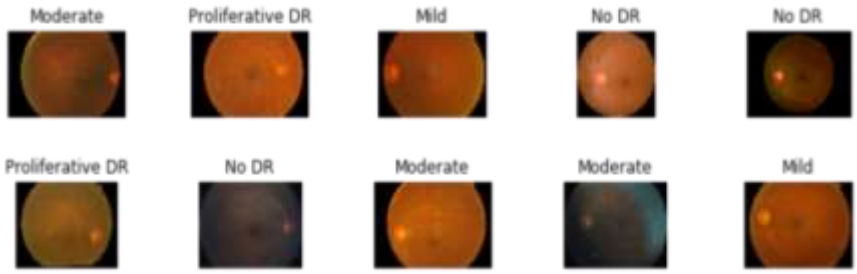


Figure 4. Retina images with labels of severity of DR

The confusion matrix for multi-class classification is shown in Figure 5, and it showcases the accurate predictions along the diagonal elements, where each row represents the true class and each column corresponds to the predicted class. Notably, the model displayed strong accuracy in recognizing no DR (587

correct predictions) and moderate DR (275 correct predictions). However, challenges emerged in distinguishing certain classes, such as no DR, with 9 instances misclassified as mild DR, and severe DR, with 28 instances misclassified as moderate DR. Overall, the matrix serves as a comprehensive evaluation tool, highlighting the model's proficiency in some classes while uncovering areas requiring further refinement.

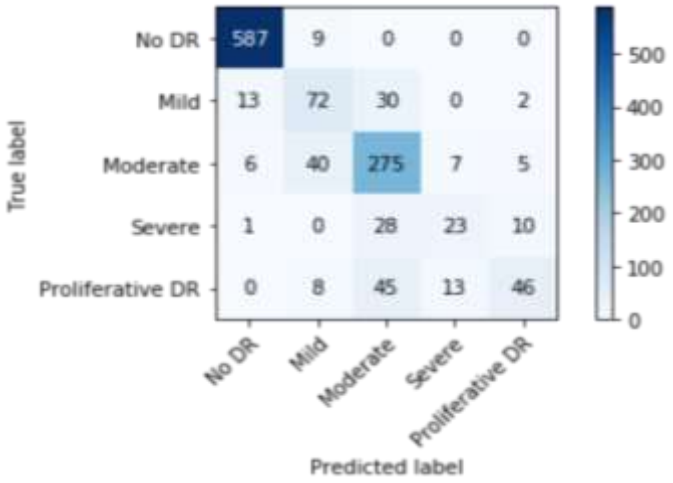
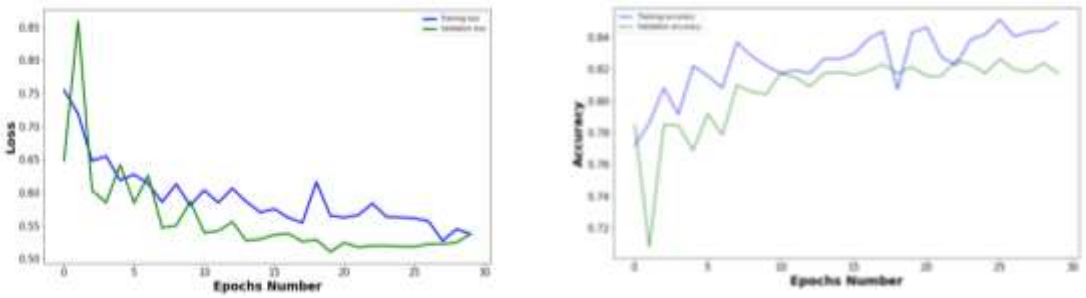


Figure 5. Confusion matrix: model predictions vs. actual class labels

The data in Table 3 represent the metrics (training accuracy, training loss, validation loss, and validation accuracy) recorded across different epochs during model training. Using these metrics, graphs were generated in Figure 6, illustrating the relationship between the numbers of epochs, the loss shown in Figure 6(a), and the accuracy shown in Figure 6(b). In this particular case, the figures display the model's performance metrics over 29 epochs, showcasing how these metrics evolve and potentially converge or diverge with each training iteration.

Table 3. Training accuracy and loss, validation loss and accuracy in each epoch

Number of epochs	Training accuracy	Training loss	Validation loss	Validation accuracy
0	0.771792763	0.755034463	0.648285182	0.785245902
1	0.786184211	0.719322748	0.858948273	0.708196721
2	0.807976974	0.648033217	0.603256721	0.785245902
3	0.791529605	0.655029376	0.584837147	0.78442623
4	0.821957237	0.618818276	0.64209849	0.768852459
5	0.815789474	0.627519772	0.584085039	0.791803279
6	0.807976974	0.613731507	0.626006479	0.778688525
7	0.836759868	0.585714199	0.54685521	0.809836066
8	0.828125	0.612917097	0.550389021	0.805737705
9	0.821957237	0.580648763	0.586297816	0.804098361
10	0.817434211	0.603748549	0.539687865	0.817213115
11	0.819078947	0.58481709	0.542103092	0.814754098
12	0.817434211	0.606531533	0.55600325	0.809016393
13	0.826480263	0.586373622	0.527535116	0.817213115
14	0.826069079	0.57024889	0.52968928	0.818032787
15	0.829358553	0.575481071	0.53653164	0.816393443
16	0.838815789	0.562178858	0.538082487	0.818852459
17	0.84375	0.55456677	0.526095138	0.82295082
18	0.807154605	0.616007655	0.528861514	0.817213115
19	0.842927632	0.565186433	0.510686069	0.821311475
20	0.846217105	0.562477249	0.524516563	0.81557377
21	0.827713816	0.566219513	0.517534104	0.81557377
22	0.822368421	0.583820187	0.519712399	0.825409836
23	0.838404605	0.563346779	0.519776312	0.82295082
24	0.841694079	0.562778491	0.518873552	0.817213115
25	0.851151316	0.561373844	0.518437012	0.826229508
26	0.840460526	0.556755711	0.522460155	0.819672131
27	0.843338816	0.527047623	0.522506847	0.818032787
28	0.844161184	0.544994791	0.524690615	0.823770492
29	0.849506579	0.537531073	0.53772449	0.817213115



(a) (b)

Figure 6. Graph shows the relationship between Epoch's number (a) loss and (b) accuracy

Table 4 presents the model's performance metrics for multiple classes: Class 0 shows high precision, recall, and F1-score, indicating accurate predictions with strong support. Class 1 struggles with lower precision and recall. Class 2 demonstrates balanced metrics. Class 3 faces challenges, resulting in a lower F1-score. Class 4 exhibits high precision but lower recall. "Macro Avg" represents average performance across all classes, while "Weighted Avg" considers class support. The accuracy stands at 0.82, showcasing the model's competency in multiclass classification.

Accuracy: accuracy measures the proportion of correctly classified instances out of the total predictions made by the model, reflecting overall predictive performance.

$$Accuracy = \frac{TN+TP}{TN+FP+FN+TP} \quad (1)$$

Precision: precision evaluates the correctness of positive predictions by the model, representing the ratio of accurately predicted positive instances to the total predicted positive instances.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall: this metric measures the model's ability to correctly identify all relevant instances in a class. It's the ratio of correctly predicted positive observations to the total actual positives.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-score: a harmonic mean of precision and recall, offering a balanced assessment.

$$F1 - Score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (4)$$

$$TP\ for\ class\ k = A_{k,k} \quad (5)$$

$$FP\ for\ class\ k = \left(\sum_{i=0}^{n} A_{i,k}\right) - A_{k,k} \quad (6)$$

$$FN\ for\ class\ k = \left(\sum_{i=0}^{n} A_{k,i}\right) - A_{k,k} \quad (7)$$

$$TN\ for\ class\ k = \left(\sum_{i=0}^{n}\sum_{j=0}^{n} A_{i,j}\right) - \sum_{i=0}^{n} A_{i,k} - \sum_{i=0}^{n} A_{k,i} + A_{k,k} \quad (8)$$

Table 4. Classification report

Class	Precision	Recall	F1-score	Support
0	0.96	0.98	0.97	596
1	0.69	0.5	0.58	117
2	0.7	0.86	0.77	333
3	0.4	0.39	0.39	62
4	0.8	0.38	0.52	112
Macro avg.	0.71	0.62	0.65	1220
Weighted avg.	0.82	0.82	0.81	1220
	Accuracy	0.82		

4.1. Comparative analysis

In this section, comparison of the disease classification model of this study with the established methodologies. The study of [16] focused on binary DR detection with high accuracy, while this research introduced a multi-class classification approach, enhancing predictive capabilities for diverse DR stages. Table 5 compares accuracy rates for diabetic retinopathy detection: CNN achieved 93.72%, XGBoost 91.40%, and DNN 95.6%.

Table 5. Comparison of different models for detection of DR

Model	Classification	Accuracy	Recall	Precision	F1-score
CNN [16]	Binary (DR/NoDR)	93.72	97.30	-	-
	Multi-class(5-classes)	-	-	-	-
XGBoost [17]	Binary (DR/NoDR)	91.40	-	-	-
	Multi-class(5-classes)	-	-	-	-
DNN [18]	Binary (DR/NoDR)	95.6	92	94	93
	Multi-class(5-classes)	-	-	-	-
DenseNet169	Binary (DR/NoDR)	98	69.90	91.45	79.22
	Multi-class(5-classes)	82	82	82	81

The proposed retinal image-based diabetes prediction model, despite its depth and high training accuracy, lacks specialized features for DR detection. The graphical representation in Figure 7, through the graph, visually underscores these findings, providing a clearer insight into the model's performance across classifications. Unlike previous binary DR classification studies, this paper's model adopts a multi-stage approach. While prior models showed high accuracy in binary classification, this model achieves an exceptional 98% accuracy. This multi-stage method enhances performance in distinguishing DR stages, reaching 82% accuracy. Multiclass classification in DR research offers insights into diverse disease stages for precise treatment planning. It discerns subtle severity differences, aiding in nuanced retinal image analysis. Models like DenseNet169 ensure high accuracy, enabling robust predictions and early interventions to prevent vision loss. Avoiding diabetic retinopathy consequences requires strict blood sugar control, regular eye exams, and timely medical intervention to prevent vision loss. DenseNet169 CNN model significantly advances diabetes detection and classification, improving diagnostic accuracy and potentially enhancing early detection and treatment outcomes.

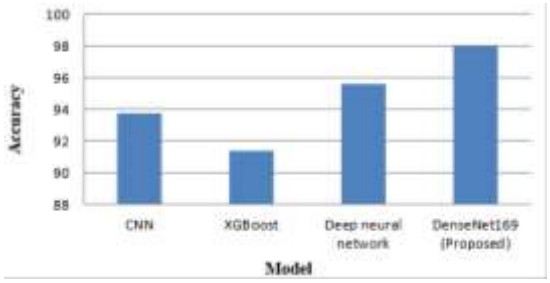


Figure 7. Graph shows the accuracy comparison of this paper proposed model with previous models

5. CONCLUSION

This study explores CNN-based methods for DR prediction and classification, aimed at blindness prevention using retinal images, leveraging DenseNet169 architecture on the APTOS 2019 dataset. With over 13,000 fundus images, the model aims to predict five diabetic retinopathy stages. Following preprocessing and feature extraction, the model achieved 82% accuracy, surpassing advanced algorithms. Evaluation encompassed accuracy, precision, recall, and F1 score metrics. This paper’s proposed model showcases substantial superiority over previous binary-class models in both binary and multi-class contexts. In binary settings, it achieves an impressive accuracy of 98%, outperforming established models. When expanded into multi-class classification, your model maintains high accuracy at 82%, marking a significant leap forward compared to traditional binary models. The proposed methodology is an ImageNet training transfer learning DenseNet model which needs huge dataset to train, and data are labelled. Transitioning from labeled to semi-labeled or unlabeled data could enhance the model's robustness and scalability, allowing for more extensive data utilization and potentially improving performance. This method enables leveraging a larger pool of data

while still maintaining some level of supervision. Combine multiple data sources and ensure the model's interpretability while collaborating with healthcare professionals for ethical and practical implementation in clinical contexts.

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