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Research Article

A Novel CNN architecture for detecting Diabetic Retinopathy

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Abstract

***Objective*:** Diabetic Retinopathy (DR) is the leading cause of preventable blindness in adults. It is the leading cause of vision loss, in people aged 50 and above. Global prevalence is projected to rise to 129.84 million by 2030 and 160.5 million by 2045. Effective management relies on regular screening and prompt intervention. With increasing demands, automated screening methods using deep learning techniques offer enhanced diagnostic accuracy and timely intervention. This study aimed to address the increasing prevalence of DR and the demand for automated screening methods, leveraging deep learning techniques to enhance diagnostic accuracy and facilitate timely intervention.

***Methods*:** In this research, a new Convolutional Neural Network (CNN) architecture is tested with the goal of accurately detecting different stages of DR. A thorough assessment of innovative CNN design, is done using various metrics such as Accuracy, Precision, Recall, and F1 score.

***Results*:** The Experimental findings indicate that the proposed CNN model surpasses existing research efforts, demonstrating its superiority in accurately predicting stages of DR. With impressive metrics such as 95% accuracy, 93% precision, 94% recall, and a 93% F1 score, this novel CNN model showcases its efficacy in precisely assessing the severity of DR and the integration of batch normalization and dropout layers into the architecture aids in mitigating overfitting, further enhancing the model's performance and generalization capabilities.

***Conclusion*:** In conclusion, the comprehensive experimentation and evaluation have established the robustness and scalability of the model, offering promising prospects for improved DR screening in clinical settings. The results emphasize the transformative potential of innovative deep learning architectures in revolutionizing DR diagnosis and management. With these advancements, the future of DR care can be predicted to improve patient outcomes and preserve vision.

Keywords: Diabetic Retinopathy. Diabetes. Retina. CNN model. Kaggle dataset.

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Introduction

Diabetes mellitus, a significant public health concern characterized by chronic hyperglycemia, has surged in both developed and developing Nations. As a result, it can lead to a condition called DR, which can cause permanent blindness in severe cases. This condition mainly arises from damage to the blood vessels that supply nutrients to the retina, a tissue sensitive to light [1]. According to the World Health Organization (WHO), around 382 million people had DR in 2013, and this number is expected to reach 592 million by 2025 [2]. Additionally, as per the International Diabetes Federation's 2021 report, there are currently 537 million cases of diabetes, projected to increase to 643 million by 2030 and 783 million by 2045 [3]. Furthermore, DR is common among certain groups of patients, with approximately 40% of type II diabetic patients and 86% of type I diabetic patients. Numerous clinical studies have demonstrated that prompt treatment and effective blood sugar management can mitigate the associated risks of DR [4].

In DR, lesions refer to abnormalities or changes in the retina. These lesions include:

1. **Microaneurysms**: Small bulges in the blood vessels of the retina.
2. **Hemorrhages**: Leakage of blood from weakened blood vessels into the retina.
3. **Exudates**: Deposits of fats and proteins leaking from damaged blood vessels.

These lesions can be observed during fundus examination using techniques such as fundus photography or fluorescein angiography, and they play a crucial role in assessing the severity of DR and guiding treatment decisions [5]. The primary aim of DR classification is to identify and grade the severity of the disease based on the International clinical DR disease severity scale. Figure 1 displays retinal images exhibiting various levels of severity in DR.

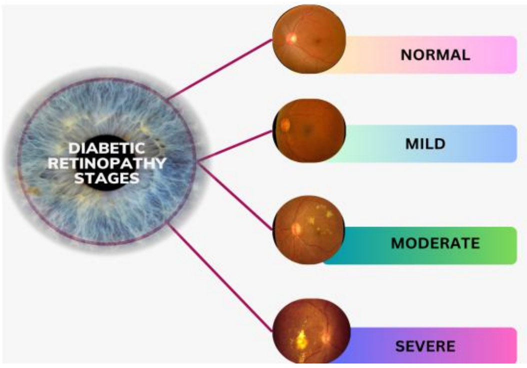

Fig.1 DR Stages

Thus, regular eye screening is imperative to safeguard vision and prevent blindness in individuals with diabetes. In clinical settings, Ophthalmologists utilize fundus photography to examine the retina for abnormalities and evaluate the severity of DR. However, manually inspecting fundus images requires expertise and effort to ensure effective DR screening. Therefore, an automated DR grading system is essential for early disease diagnosis which analyzes retinal images efficiently, making screening accessible, reducing the burden on healthcare professionals, and utilizing AI advancements for accurate diagnosis, ultimately preventing vision loss. The standard grading protocol for assessing the severity of DR can be classified into four stages: No DR (Class-1), Mild DR (Class-2), Moderate DR (Class-3), and Severe DR (Class-4).

Artificial Intelligence (AI) holds promise in aiding primary Ophthalmologists in diagnosis by leveraging comprehensive medical data, thus introducing novel strategies to enhance the diagnostic and treatment standards for eye diseases in primary healthcare facilities [6]. The integration of AI with ophthalmological medical practices aims to address the practical requirements of a considerable patient population afflicted with fundus diseases. Traditional image feature extraction methods rely heavily on researchers' prior knowledge, posing significant limitations [7]. However, in recent years, the rapid advancements in deep learning models within the realm of computer vision have substantially outperformed traditional approaches. Of particular significance is the CNN model, renowned for its robust representation capabilities, which mitigate the drawbacks associated with conventional feature extraction methods [8]. Challenges persist in obtaining adequate authentic fundus images, especially concerning rare fundus diseases. Furthermore, with limited data available and the presence of inherent image noise, training a single model to attain optimal accuracy in disease detection becomes challenging [9].

Considering the existing challenges, the Novel CNN has undergone comprehensive design and optimization. This work is notable for its comprehensive analysis and refinement of a CNN architecture designed specifically to increase the accuracy and efficiency of classifying different stages of DR. This architectural innovation could involve novel layer topologies, activation functions, connection patterns, that enhance the network's ability to learn.

This paper is structured as follows: The second section begins by introducing the related works. In the third section, a detailed explanation of the materials and methods utilized in this work is provided. The experimental results are then presented and discussed in the fourth section. Finally, the fifth section offers conclusions.

Related Works

Currently, CNN models are extensively utilized in classification tasks, yielding higher accuracy rates. This literature review discusses how CNN models have been employed in identifying DR stages. The concept of AI is introduced in 1956 [10]. Shortly after, Arthur Samuel proposed machine learning (ML) in 1959, emphasizing the importance of ML's capacity to acquire statistical techniques without explicit programming. Deep learning (DL) emerged as a subset of ML, predominantly employing multi-layer neural networks. Among DL models, CNN stand out for image processing, comprising convolutional layers, pooling layers, and fully connected layers. Widely recognized CNN architectures include AlexNet, VGGNet, Inception V1–V4, ResNet, and DenseNet. These CNN models are trained end-to-end on labeled image datasets, enhancing accuracy by adjusting parameters through error backpropagation algorithms based on predefined objective functions. Another significant ML technique is transfer learning, wherein a model is initially trained in a source domain, and then fine-tuned in a target domain. This approach enables effective learning with good generalization capabilities, particularly beneficial for domains with limited data. DL offers a key advantage over traditional ML by automatically learning diverse levels of semantic feature representations from large-scale datasets.

In [11], the utilization of GoogleNet, ResNet, DenseNet, and VGG-16, is emphasized followed by a comparative analysis to determine the most optimized variant. Since all transfer learning networks are extensively pre-trained, the dataset necessary for implementation is significantly reduced. Initially, all fundus images are pre-processed and resized to 224 x 224 pixels before being input into the subsequent layers. Upon comparison, it is noted that the Inception model achieved the highest accuracy, reaching 82 percent. Similarly, the approach described in [12] is focused on assessing the quality of fundus images during their acquisition process. It employs a Deep CNN (DCNN) architecture comprising five convolutional layers, two fully connected layers, and a binary classification layer, trained to automatically evaluate image quality. The initial convolutional layer of the DCNN is composed of 96 filters sized 11×11, followed by 256 filters in the second layer, 384 filters in both the third and fourth layers and 256 filters in the final layer. The activation size of the first and last fully connected layers is 4096 filters, resulting in a final output fully connected layer producing a 4096-dimensional image. In addition to this in [13], a comparison between the InceptionV3 and Xception architectures is conducted to classify DR into two categories: DR or No DR, utilizing the Waggle dataset. The researchers utilized the entire dataset comprising 35, 126 images, allocating 20% of the

images for testing the algorithm's performance. Fine-tuning the last two blocks of the two architectures, they compared two optimizers with varying learning rates: stochastic gradient descent and Adam. Image augmentation techniques such as horizontal and vertical flipping, as well as shifting and rotating the images, were employed to enhance the model's robustness. The evaluation metric used to gauge the architectures' performance was accuracy. The reported accuracy results were 87.12% for the InceptionV3 architecture and 74.49% for Xception.
Moreover, in [14] an ensemble CNN architecture is introduced aimed at improving the efficiency of classification. Initially, they identified the most effective CNN model from a selection of eight architectures, namely InceptionResNetV2, MobileNetV2, DenseNet201, Xception, ResNet152V2, NASNetLarge, VGG16, and VGG19. Subsequently, data augmentation techniques such as rotation, width shift, and height shift were applied during the training phase of the CNN models. Thirdly, an ensemble CNN architecture was constructed using the three CNN models identified in the first step. For the ensemble learning approach, they proposed the weighted average method, and consequently, suggested the use of a grid-search method to optimize the weighted parameters. Experimental results demonstrated that the ensemble CNN architecture achieved an accuracy of 92.80%. On the same note, in [15] an ensemble learning is proposed which offers a solution to the limitations of deep learning by making predictions through multiple models instead of relying on a single model. Their experiment demonstrated promising results, achieving an accuracy of 95%. Hence this work aims to leverage a Novel CNN architecture for DR stage classification, with the objective of enhancing the accuracy of the model.

Materials and Methods

The proposed methodology aimed at constructing a system for the automated detection of DR diseases. Hence a customized neural network is constructed via training from scratch. Consequently, the detailed architecture of the network along with the specific implementation steps of the framework is elaborated below.

Novel CNN Architecture

CNN has achieved remarkable success in the field of fundus images due to its powerful feature learning ability. Neural networks are computational models formed by connecting simple computational units, called neurons, in specific patterns. They can, in principle, mimic the behaviours of any given function if there are enough neurons. CNNs represent a special type of neural network proposed by LeCun in 1990 [16]. Due to their superior performance in image-oriented tasks, they have become the mainstream model for image-related tasks. Generally, CNN layers can be classified into two categories: primary layers and secondary layers. The primary layers constitute the main components of the CNN and include convolution layers, activation layers, pooling layers, flatten layers, and dense layers. Secondary layers are optional layers that can be added to enhance CNNs' robustness against overfitting and increase their generalizability. These include dropout layers, batch normalization layers, and regularization layers [17].
The Novel CNN Architecture is structured with careful consideration of various hyperparameters to facilitate effective classification of DR Stages.
In the literature [24], the CNN architecture was observed to resemble a modified version of VGG-19. This modification entailed the addition of two convolutional layers, each followed by rectified linear units, inserted into the middle two stages. Furthermore, the final fully connected layer, originally comprised of 1000 neurons, was substituted with a three-neuron layer. The output from the five stages of convolutional layers was subsequently directed into a sequence of two fully connected layers, each containing 4096 neurons. For non-linear classification, the last fully connected layer featured 3 neurons. Additionally, a dropout layer was implemented on the outputs of the initial two fully connected layers, resulting in the dropping of 50% of the outputs. This dropout mechanism aimed to further mitigate overfitting and enhance the robustness of the architecture.
In reference to the current research, a CNN architecture is proposed, which begins with a convolutional layer that employs 32 filters of size 3x3, allowing the input data to undergo spatial convolution while maintaining dimensions through 'same' padding and a stride of 1 as shown in Figure 2.

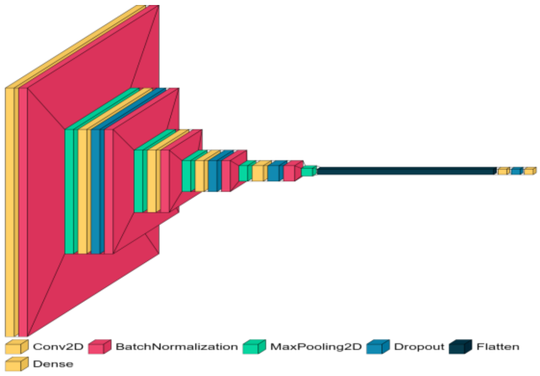

Fig.2 Novel CNN Architecture

Batch normalization is then applied to standardize activations, thereby enhancing the stability and speed of training. Subsequently, max pooling with a 2x2 window and a stride of 2 is utilized to reduce spatial dimensions, aiding in feature extraction while minimizing computational load. Following this, a dropout layer is introduced, strategically positioned after the first convolutional block to prevent overfitting and improve generalization. The detailed summary of the Novel CNN Architecture is provided in Table 1.

Table 1 The Layers and the Model Parameters used in the Novel CNN Architecture

S.No.	Layer	Model Parameters
1	Convolutional	Filters: 32, Kernel Size: 3x3, Strides: 1, Padding: 'same'
2	Batch Normalization	-
3	Max Pooling	Pool Size: 2x2, Strides: 2, Padding: 'same'
4	Dropout	Rate: 0.1 (after the first convolutional block)
5	Convolutional	Filters: 64, Kernel Size: 3x3, Strides: 1, Padding: 'same'
6	Batch Normalization	-
7	Max Pooling	Pool Size: 2x2, Strides: 2, Padding: 'same'
8	Convolutional	Filters: 64, Kernel Size: 3x3, Strides: 1, Padding: 'same'
9	Batch Normalization	-
10	Max Pooling	Pool Size: 2x2, Strides: 2, Padding: 'same'

11	Convolutional	Filters: 128, Kernel Size: 3x3, Strides: 1, Padding: 'same'
12	Dropout	Rate: 0.2 (after the fourth convolutional block)
13	Batch Normalization	-
14	Max Pooling	Pool Size: 2x2, Strides: 2, Padding: 'same'
15	Convolutional	Filters: 256, Kernel Size: 3x3, Strides: 1, Padding: 'same'
16	Dropout	Rate: 0.2 (after the fifth convolutional block)
17	Batch Normalization	-
18	Max Pooling	Pool Size: 2x2, Strides: 2, Padding: 'same'
19	Fully Connected	Units: 128, Activation: ReLU
20	Dropout	Rate: 0.2
21	Fully Connected	Units: 4, Activation: Softmax

The architecture maintains a consistent approach throughout its design, utilizing a series of convolutional blocks. These blocks are pivotal in processing the input data, gradually expanding the complexity of feature extraction by incrementally increasing the number of filters employed. This progressive augmentation, first to 64 filters and subsequently to 128, allows for a more subtle understanding of the underlying features present in the dataset.

To ensure the stability and prevent the model from overfitting to the training data, batch normalization and dropout layers are strategically integrated after each convolutional block. Batch normalization standardizes the inputs to each layer, making the optimization process more efficient and reducing the likelihood of the model becoming overly sensitive to small changes in the input data. Dropout layers, on the other hand, temporarily deactivate a proportion of neurons during training, preventing them from becoming overly reliant on specific features and enhancing the generalization capability of the model.

Once the data has been processed through the convolutional layers and pooling operations, it undergoes flattening to transform the multidimensional feature maps into a format suitable for input into fully connected layers. These dense layers serve as the core of the model, leveraging their ability to capture complex patterns within the data. The initial dense layer with 128 units, employs Rectified Linear Unit (ReLU) activation to introduce non-linearity into the model. This activation function facilitates the model's ability to capture complex, nonlinear state present in the data, enhancing its capacity to learn and generalize effectively.

A challenging aspect of the design is the deliberate elevation of the dropout rates to 20% after the fourth and fifth convolutional blocks. This adjustment is aimed at further mitigating overfitting while retaining crucial features necessary for accurate classification. By intermittently dropping out a higher proportion of neurons at these stages, the model is encouraged to focus on the most salient features present in the data, thus promoting better generalization to unseen data.

Finally, the architecture terminate in a dense layer comprising 4 units, employing softmax activation to produce output probabilities for the classification task. These probabilities represent the model's assurance in assigning input data to one of the four target classes, providing valuable insights into the model's decision-making process and enabling effective categorization of input samples.

Implementation details

a) Experimental setup

(i) Hardware

The model implementation and training utilize a system equipped with an NVIDIA Tesla K20 GPU with 5 GB of memory. It operates on Windows 10, supported by a 64-bit Intel i3 processor.

(ii) Software

To implement pre-trained architectures using an open-source language, this work suggests utilizing TensorFlow. TensorFlow, an open-source self-learning platform primarily created by Google and based on Python, provides a comprehensive array of libraries. One of these is Keras, a Python deep learning application programming interface (API) built on TensorFlow. Keras simplifies the creation of equivalent models effortlessly.

(iii) Integrated Development Environment (IDE)

The experimental evaluation takes place within the Jupyter Notebook environment.

b) Data collection

The research utilizes an open-source DR detection dataset sourced from Kaggle [18], comprising 2834 images. The classification task involves sorting the images into four classes: No DR, Mild DR, Moderate DR, and Severe DR, graded on a scale of 0–3 (0-No DR, 1-Mild, 2-Moderate, 3-Severe) to denote varying severity levels. Additionally, the dataset is partitioned to accommodate the model, with specifics of the split provided in Tables 2 and 3, indicating the number of retinal images in Validation Set available for each severity level.

Table 2 The details of DR Dataset

Dataset subsets	Number of Images in Kaggle dataset
Training set	1984
Validation set	850

Table 3 The number of retinal images available in the Validation Set for each DR Stages

Severity level	Number of images in Validation Set
Class-0 (normal)	211
Class-1 (mild stage)	213
Class-2 (moderate stage)	214
Class-3 (severe stage)	212
Total	850

c) Evaluation metrics

Accuracy serves as the most fundamental evaluation metric in classification tasks, representing the proportion of correctly classified samples. Precision denotes the likelihood of correctly identifying positive samples out of all samples predicted as positive. Recall, on the other hand, pertains to the likelihood of correctly identifying positive samples out of all actual positive samples. The F1 score, a commonly used evaluation metric for classifiers, amalgamates precision and recall, providing a balanced performance measure for classification tasks [19]. Certainly here are the equations (1), (2), (3) and (4) for these Performance Metrics,

$$\text{Accuracy} = \frac{\text{True Positives}+\text{True Negatives}}{\text{True Positives}+\text{False Negatives}+\text{True Negative}+\text{False Positives}} \quad \textbf{(1)}$$

$$\text{Sensitivity} = \text{Recall} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Negatives}} \quad \textbf{(2)}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}} \quad \textbf{(3)}$$

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

Results and Discussion

Table 4 shows the performance comparison of the existing CNN architectures and the proposed CNN architecture. Among the models tested, the Novel CNN model exhibited the highest accuracy with a score of 0.95, showcasing its effectiveness in classifying DR stages.

Table 4 The Metrics of the Proposed Model compared with Existing Works

S.No.	Model	Accuracy	Precision	Recall	F1 Score
1	Pratt [20]	0.75	-	-	-
2	Pradeep Kumar Jena [24]	0.9360	0.9188	0.8206	0.8669
3	**Proposed Novel CNN Model**	**0.9541**	**0.9336**	**0.9463**	**0.9398**

A confusion matrix is a tabular representation that illustrates the effectiveness of a classification model. It presents a summary of both correct and incorrect predictions made by the model, differentiating between True Positives, True Negatives, False Positives, and False Negatives. While Figure 3 depicts the Confusion Matrices of the Novel CNN Architecture, this matrix furnishes valuable insights into the classification model's performance.

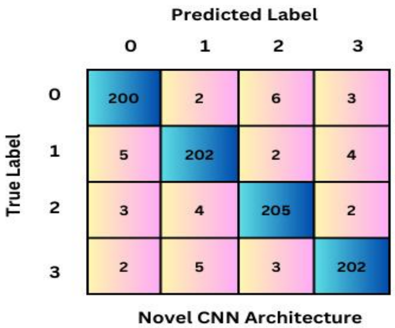

Fig.3 Confusion Matrix of Novel CNN Architecture

The Figure 4 illustrates the losses and validation loss of a Novel CNN Model across 10 epochs. The training loss demonstrates a continual decrease in loss values during training, highlighting its ability to adapt and refine parameters to minimize loss throughout dataset iterations. Concurrently, the validation loss consistently diminishes as training progresses. This significant reduction in validation loss suggests that the Novel CNN Architecture effectively learns from the training data, thus improving its performance in DR Classification.

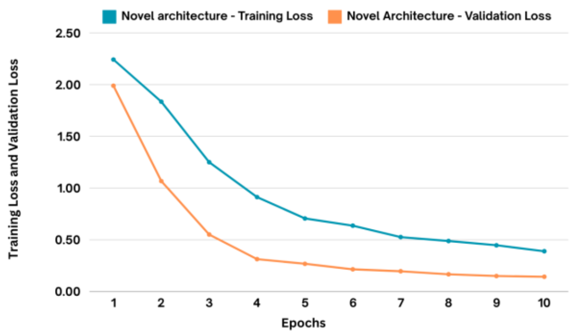

Fig.4 Training Loss and Validation Loss per Epoch of Novel CNN Model

The Figure 5 illustrates the Novel architecture model consistently maintains its accuracy, achieving a score of 0.97. This suggests a high level of precision, as the model's predictions closely match the actual outcomes. Similarly, during the validation phase, the accuracy of the Novel architecture remains consistently high, with a score of 0.95, indicating the model's reliability throughout validation. Thus, the high validation accuracy of the novel CNN architecture demonstrates its successful ability to precisely categorize DR images based on the learned features during training.

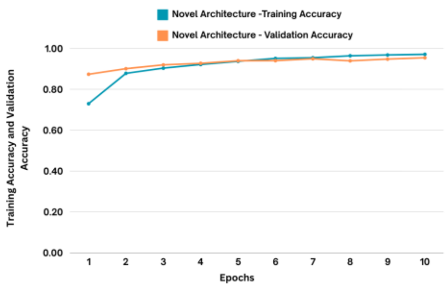

Fig.5 Training Accuracy and Validation Accuracy per Epoch of Novel CNN Model

Several research papers in the area of CNN have evolved for the automated detection of DR [20, 21, 22, 23, 24]. CNN methodologies are firmly established and applicable across various medical applications as well as beyond the medical domain.

In order to classify and stage DR, a deep CNN architecture with 18 convolutional layers and 3 fully linked layers was employed in the study [24]. Three categories for the subjects were no DR, moderate DR, and severe DR. A total of 4,600 fundus images were generated from the original Waggle dataset, utilizing a class-specific data augmentation technique.The proposed network was trained and tested on these images using 5-fold and 10-fold cross-validation techniques. The study discovered a few drawbacks too. Firstly, the CNN model could only classify DR into three categories, combining mild and moderate NPDR into one group, and severe NPDR and PDR into another. Secondly, the perception of neural network models as "black boxes" generally makes it difficult to understand the extracted characteristics or results. SVM techniques, on the other hand, extract customized features that help medical professionals find DR biomarkers. CNN is one of the deep learning methods that is prone to overfitting. When a model is trained on a small dataset, it becomes overfitted and performs inadequately on additional data. To mitigate this, 5- and 10-fold cross-validation were used in conjunction with class-specific data augmentation to reduce overfitting and offer an unbiased evaluation on the given dataset.

However the proposed Novel CNN architecture outperforms the above literature due to several factors. Firstly, the proposed CNN can classify the DR Stages into four categories. This happens because convolutional layers efficiently capture hierarchical features from input images by employing multiple layers of convolutions with varying filter sizes, allowing the model to detect patterns at different levels of abstraction. Additionally, max-pooling layers aid in down sampling feature maps, preserving crucial information while reducing computational complexity and preventing overfitting, thereby enhancing spatial hierarchical representation within the images. Furthermore, the utilization of dropout layers helps prevent overfitting by randomly dropping neuron units during training, promoting the learning of redundant representations, and improving generalization ability. Batch normalization layers stabilize and expedite the training process by normalizing activations, leading to faster convergence and better performance. The incorporation of 'same' padding in convolutional and max-pooling layers ensures the preservation of spatial dimensions, crucial for retaining important information near input image borders during operations. Moreover, the architecture is designed to scale with dataset complexity, allowing for the learning of intricate features and patterns through increased filter and layer count. The use of ReLU activation functions introduces non-linearity, enabling the model to learn complex decision boundaries and better represent underlying data distributions. Lastly, Softmax activation in the final layer facilitates multi-class classification tasks by converting raw scores into probabilities, aiding in easy interpretation and decision-making. In summary, this CNN architecture exhibits robustness, efficiency, and adaptability, making it well-suited for a wide range of image classification task.

Conclusion

The research concentrates on developing an innovative CNN architecture tailored for detecting DR with notable success being demonstrated on a publicly available dataset from Waggle. Following the experiments, the bespoke CNN techniques undergo rigorous evaluation based on key metrics including Accuracy, Precision, Recall, and F1-Score. The experiment results show that the customized CNN attains a remarkable 95% accuracy rate, 93% precision, 94% recall, and a 93% F1 score. This result clearly shows that the CNN architecture is superior in identifying DR since it performs well in classification tasks with minimal error. Future work will also concentrate on implementing the proposed model for practical usage in order to verify its effectiveness and collaboration with medical experts is essential. This validation procedure encompasses evaluating the model's efficacy in detecting DR using Novel, unseen data. Medical specialists will scrutinize the model's predictions against verified ground truth labels, ensuring its accuracy, sensitivity, specificity, and overall reliability within clinical environments.

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Authors contributions
The corresponding author contributed to the study conception, design, data collection and analysis. The first draft of the manuscript was written by K.Santhiya Lakshmi. The second author Dr.B.Sargunam read and approved the final manuscript.

Data availability
All analysis-based data generated in the study have been included in the manuscript and the dataset used in the study is available in the Kaggle platform.

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Declarations
Conflict of interest
The authors declare that they have no competing interests.

Consent to participate
Informed consent was obtained from authors included in this study.

Consent for publication
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