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Classification of Diabetic Retinopathy Using Cnn

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Abstract: Diabetic retinopathy affects individuals with diabetes. Diabetes is a prevalent global disease. Currently, about 422 million people have diabetes, putting them at risk of developing diabetic retinopathy, a condition can lead to vision loss or blindness. 25% of diabetics also have diabetic retinopathy, with 5% experiencing complete vision loss. Symptoms include seeing spots or dark floaters, blurry vision, fluctuations in vision, dark or empty patches in vision, and eventual vision loss. The aim of this study is to explore various deep learning techniques using Fundus images for diabetic retinopathy detection. Our project involves utilizing pre-trained CNN models like VGG16 and RESNET50, along with building a CNN model from scratch for multi-level classification of diabetic retinopathy. Features extracted from these models will be used with machine learning classifiers to categorize subjects into different levels of diabetic retinopathy severity. Additionally, transfer learning methods will be employed to address data limitations and enhance training efficiency. The effectiveness of our approach will be evaluated on 80% of the training dataset. We believe that our research can assist ophthalmologists in diagnosing and treating patients more efficiently before the condition worsens.

Important Keywords *Diabetic retinopathy, CNN, Fundus Images, Deep Learning, Transfer learning.*

Introduction:

Diabetic eye disease (DED) is a greatly feared complication of diabetes. Primarily, it involves diabetic retinopathy (DR). Across most nations, DR is recognized as one of the leading causes of blindness among working-age individuals. This condition brings not just personal distress but also serious socioeconomic repercussions. In 2019, a comprehensive review was conducted to assess the incidence of DR. The analysis drew from eight studies carried out post-2000, spanning five from Asia, and one each from North America, the Caribbean, and Sub-Saharan Africa. The findings revealed that the annual incidence of DR ranged between 2.2% to 12.7%. Additionally, annual progression to severe stages (STDR) varied from 3.4% to 12.3%. This review underscored the urgent need for further high-quality, population-based studies. Building a robust evidence base is crucial for developing effective public health strategies—including screening programs—for managing DR efficiently [1]. Micro-aneurysms occur due to elevated blood sugar levels, which cause walls of tiny blood vessels to distend. As the condition progresses, these micro-aneurysms rupture, leading to retinal haemorrhages in either superficial or deeper layers of the retina. The vessels not only leak blood but also allow lipids and proteins to escape, resulting in the formation of small bright dots as exudates Should this phenomenon occur the macula region, vision may ensue (Fig.1). Further advancement of the disease, numerous small patches of the retina become ischemic, meaning they are deprived of adequate blood supply. These ischemic areas manifest on the retina as fluffy whitish spots called cotton wool spots [2] (Fig.2).

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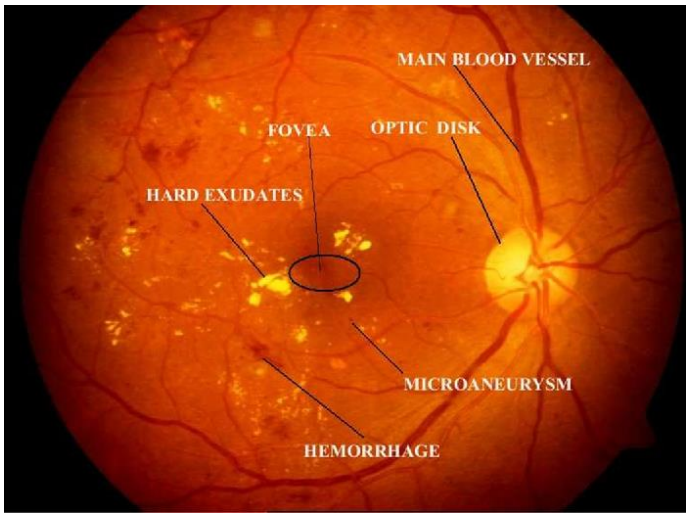

Fig.1 An image containing micro-aneurysm, haemorrhage and hard exudates

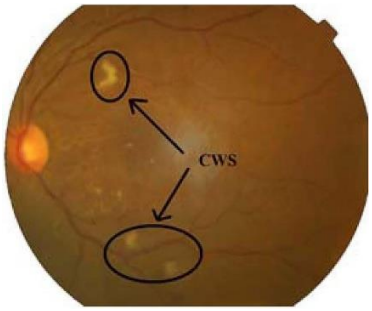

Fig.2 Diabetic Retinopathy with cotton wool spots.

Suggested Methodology:

The recognition & analysis of human disease by software or devices can be risky. It occurs online or offline. The process starts with receiving fundus images for input into preprocessing. Dataset collection involves Retinal images focusing on Diabetic Retinopathy cases. These images are used for the CNN model. Preprocessing includes resizing, normalization, and categorization for uniformity and model enhancement. Images are then divided into training, testing, and validation sets. The CNN architecture is key in detecting Diabetic Retinopathy patterns. Characteristic feature extraction is vital in classification. Classification methods include CNNs, SVMs, RNNs, deep belief networks, deep Boltzmann machines, and KNN. We are using CNN classification model VGG16 and RESNET50 . After training, the evaluation phase commences. The trained CNN model is tested with retinal images to measure performance quantitatively using metrics like accuracy.

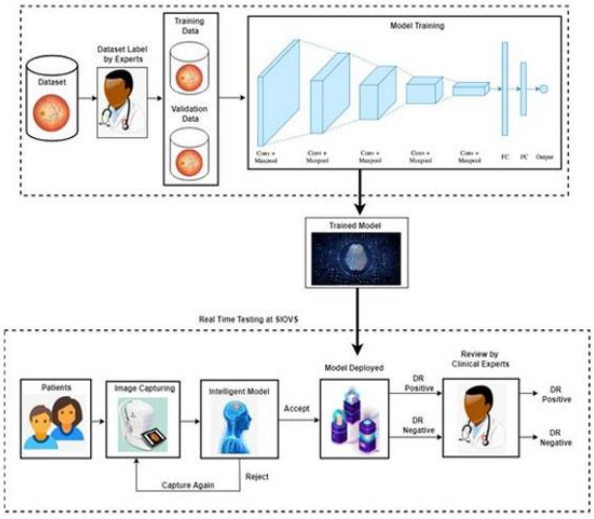

Fig. 3 Block Diagram of Methodology.

Working Principle

The convolutional neural network (CNN) model is trained using a deep learning approach. It utilizes a dataset comprising 3662 images taken from a publicly available dataset in kaggle [3]. This dataset is methodically split into two primary sections: training and testing. Specifically, 80% of the total dataset is allocated for training purposes, while the remaining 20% is designated for testing. In addition, the training dataset undergoes further segregation into training & validation subsets. The customized model undergoes initial training on the primary training dataset [4]. Subsequently, it receives images from the validation set to assess accuracy and loss. Our customized CNN model extracts features from pre-processed images before being fed into the CNN architecture. After the training phase, when an image is supplied to the model, it classifies the severity of Diabetic Retinopathy (DR). The classification includes categories such as no DR, mild, moderate, non-proliferative, and proliferative [5]

Designing and implementing custom CNN model

In this study, our CNN model consisted of 7 convolutional layers, 4 average pooling layers, ReLU layers, dropout layers & full connection (FC) layers. The input image size is (128, 128, 3). The convolutional layer is the first layer of our deep learning framework—it was crucial for extracting textual features. The diagram depicting the convolutional process is illustrated (Figure 4). As shown in Figure 4, the top-left window represents a patch of the input image matrix; the top-right denotes a designed convolutional kernel, and the right window exhibits the output feature map after the convolution process. In our CNN models, there were multiple kernels designed to capture features from varying directions. The normalization layer, also known as the rectified linear units (ReLU) layer, applies an elementwise activation function—such as max (0, x) which thresholds at zero:

$$f(x) = \max(0, x)$$

in which x represents the number of neurons [6].

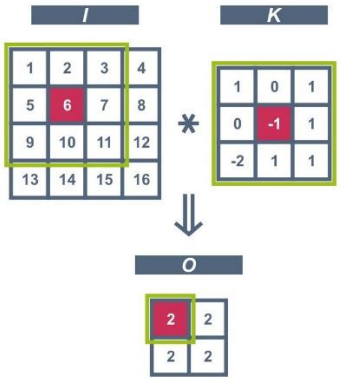

Fig. 4 Diagram of Convolutional Process

Pooling layer is an important layer inside CNN. It could prevent over-fitting and down-sampling of the feature matrix size. In this study, we are using average pooling.

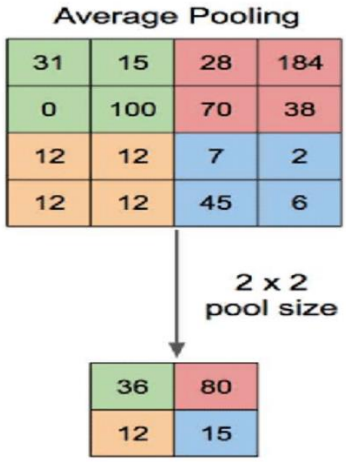

Fig. 5 Diagram of average pooling process.

Minimizing an error function, also called the loss function, is how learning in neural networks happens. This function measures the difference between Expected outputs and calculated outputs on the complete sample. If an error is close to 0, it means the network classifies data correctly. For achieving this, optimizers are employed. For this investigation, we employ the ADAM optimization algorithm [7]. The term "Adam" is derived from "adaptive moment estimation," emphasizing its capacity to flexibly modify the learning rate for individual network weights. In contrast to Stochastic Gradient Descent (SGD), which employs a uniform learning rate throughout training, Adam calculates distinct learning rates dynamically. This process is based on historical gradients and their second moments, allowing for personalized adjustments to each network weight. The creators of Adam drew beneficial features from other algorithms like AdaGrad & RMSProp. Similar to RMSProp, Adam considers the second moment of gradients; however, unlike RMSProp, it does not subtract the mean when calculating the variance of gradients. By incorporating both the first moment (mean) and second moment (uncentered variance) of gradients, Adam achieves an adaptive learning rate, which effectively navigates the optimization landscape during training. This adaptiveness aids in faster convergence and enhances neural network performance significantly.

Adam optimizer formula:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] \; v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2$$

Where,

m_t = aggregate of gradients at time t [current] (initially, mt = 0)

m_t-1 = aggregate of gradients at time t-1 [previous]

W_t = weights at time t

W_t+1 = weights at time t+1

A_t = learning rate at time t

∂L = derivative of Loss Function

∂W_t = derivative of weights at time t

β = Moving average parameter (const, 0.9)

The Adam optimizer builds on the strengths of its predecessors, significantly outperforming them in gradient descent optimization. With a learning rate of 0.001, it demonstrates notably enhanced performance compared to previously utilized optimizers, offering substantial improvements in efficiency [8].

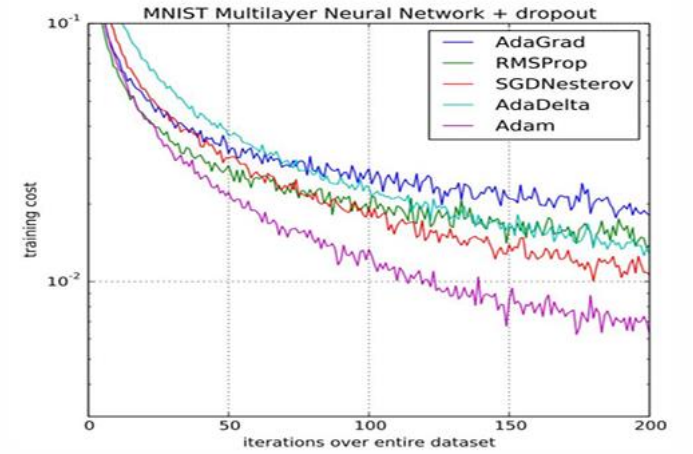

Fig. 6 Performance Comparision on training cost.

The learning rate of 0.001 determines the step size at each iteration while moving toward a minimum of the loss function. A total of 100 epochs is given. The learning rate is reduced by a factor of 0.5 if the validation accuracy has not improved for 4 epochs. We also ensured that the training process will stop if the validation loss doesn't improve for 10 consecutive epochs (Early Stopping).

Classification Accuracy is the evaluation metric used in this model. The metric is calculated by dividing the number of accurately predicted outcomes by the total quantity of input data points.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

Fig. 7 Accuracy Formula

Confusion matrix is also observed for the better understanding of the total performance of the model. It consists of 4 important terms, namely

- **True Positives** : The cases in which the model predicted YES and the actual output was also YES.
- **True Negatives** : The cases in which the model predicted NO and the actual output was NO.
- **False Positives** : The cases in which the model predicted YES and the actual output was NO.
- **False Negatives** : The cases in which the model predicted NO and the actual output was YES [8].

$$Accuracy = \frac{TruePositive + TrueNegative}{TotalSample}$$

Fig. 8 Accuracy of the confusion matrix.

Transfer learning:

Transfer learning involves a source domain (D_s) with its associated task (T_s) and a target domain (D_T) with its corresponding task (T_T). The aim is to enhance the predictive capabilities of the target function ($f_T(\cdot)$) by leveraging relevant data from both D_S and T_S. This approach requires that D_S and D_T, or T_S and T_T, are not identical. While this concept initially focuses on a single source domain, it can be expanded to encompass multiple source domains. Within the context of transfer learning, the source domain (DS) and target domain (DT) are represented as {XS, P(XS)} and {XT, P(XT)}, respectively. When D_S is not equal to D_T, it indicates that either X_S differs from X_T or the probability of X_S is not the same as the probability of X_T. When $X_S \neq X_T$ within this paradigm, it is classified as heterogeneous transfer learning. Conversely, when $X_S = X_T$, it is termed homogeneous transfer learning. [9].

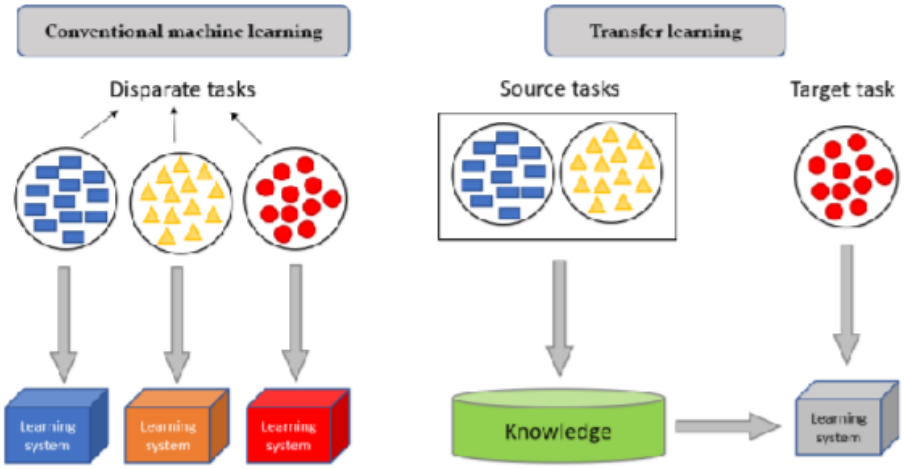

Fig. 9 Comparative diagram of Learning processes between conventional machine learning and Transfer learning.

Different pre-trained models used:

ImageNet stands as a notable research initiative aimed at constructing a vast repository of images annotated with labels. Examples include images linked to their corresponding categories. Pretrained models such as InceptionV1, Inception V2, VGG-16 ResNet-50, & VGG-19 have undergone training on ImageNet, which encompasses diverse image categories. These models are meticulously built from the ground up and trained utilizing powerful GPUs. The training process involves millions of images spanning thousands of categories. Because the dataset is so extensive, these models have developed an excellent understanding of low-level features like spatial properties, edges, rotations, lighting, and various shapes. Such features facilitate knowledge transfer and can function efficiently as feature extractors for new images encountered in different computer vision challenges. Notably, these new images can belong to entirely different categories from those in the source dataset. Nevertheless, thanks to principles underlying transfer learning, pretrained models should still be capable of extracting pertinent features from these new images. This paper aims to harness the efficacy of transfer learning by employing the pretrained model VGG-16 and ResNet-50 along with custom CNN model. These models will serve as a potent feature extractor to classify the severity of diabetic retinopathy disease accurately [10].

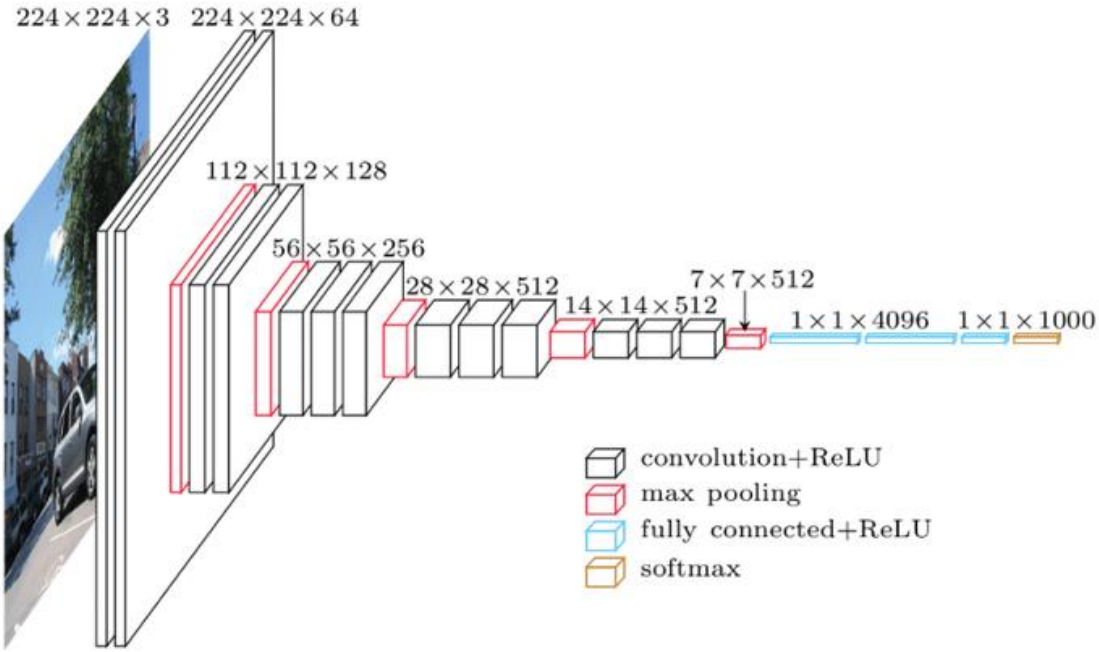

Fig. 10 VGG16 architecture.

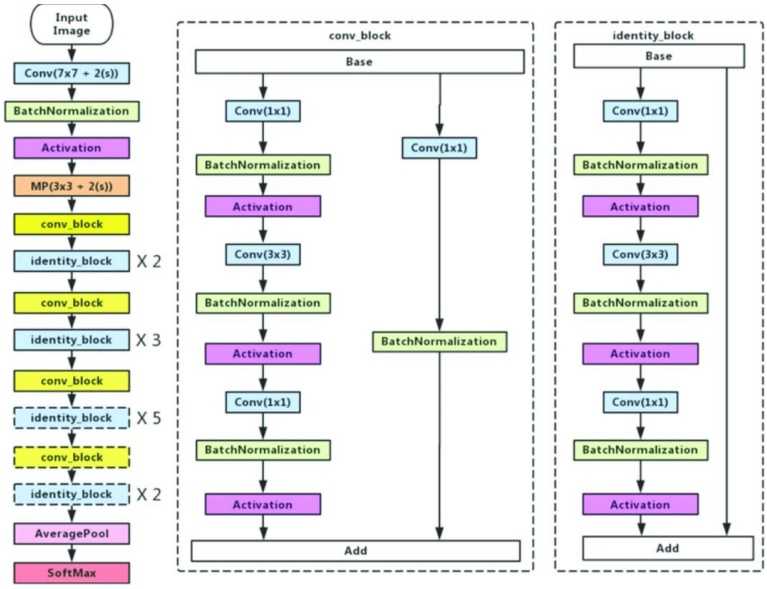

Fig. 11 ResNet-50 Architecture

Analysis:

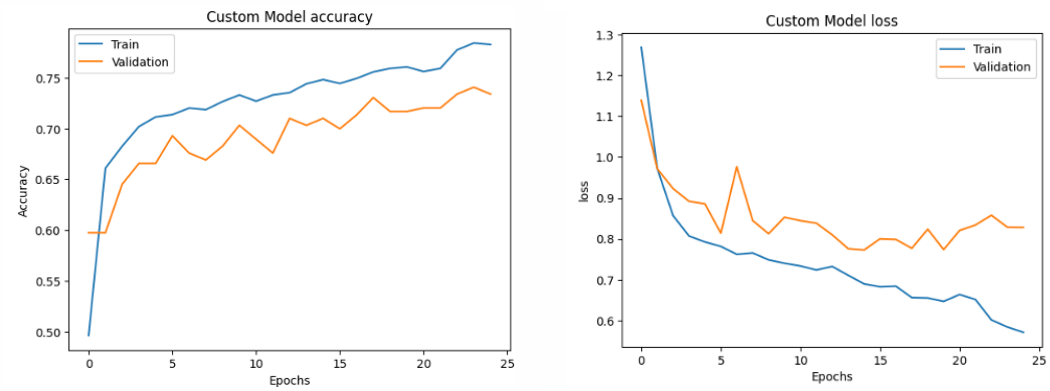

Fig. 12 Custom CNN accuracy and loss plot

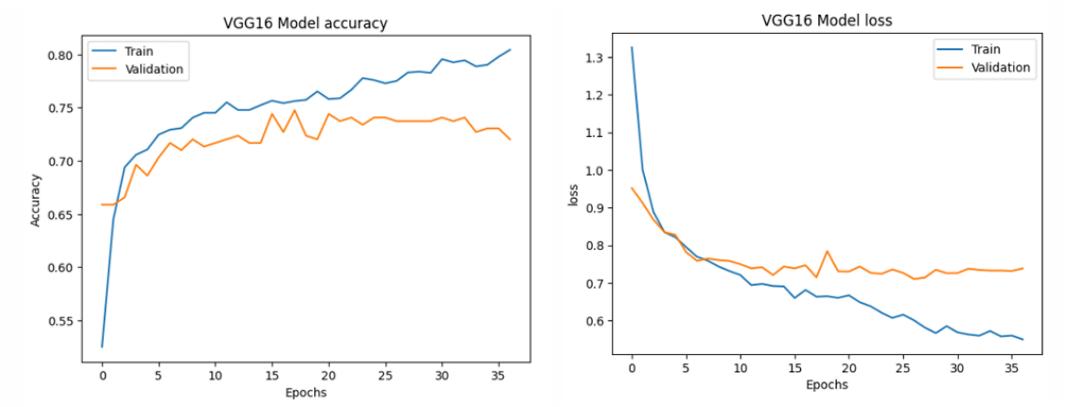

Fig. 13 VGG16 accuracy and loss plot

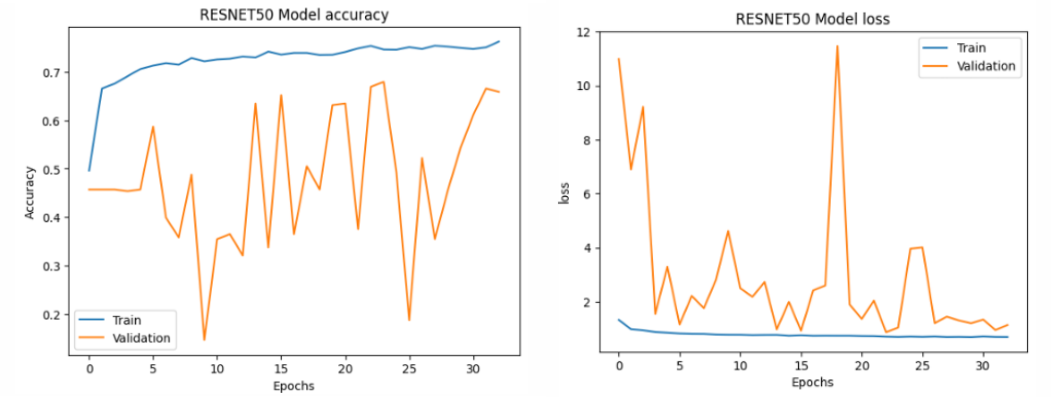

Fig. 14 RESNET50 accuracy and loss plot

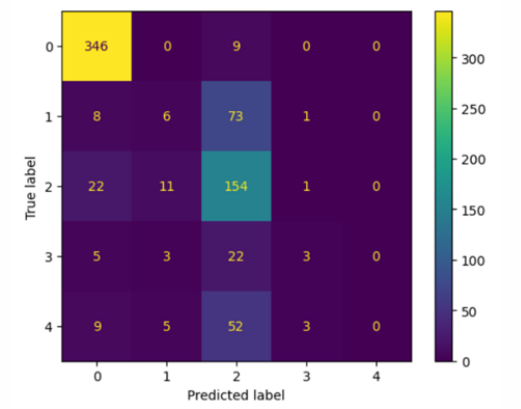

Fig. 15(a) Confusion matrix of Custom CNN

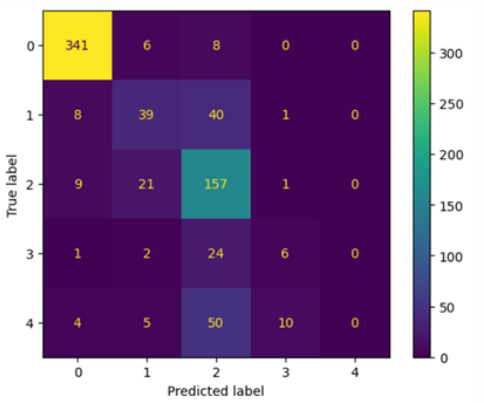

Fig. 15(b) Confusion matrix of VGG16

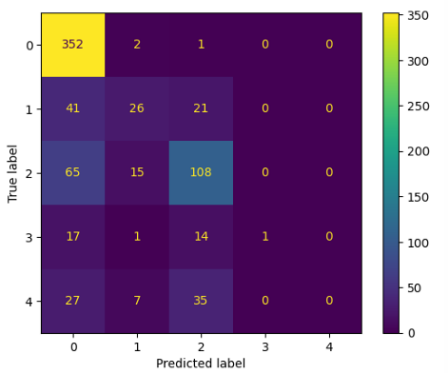

Fig. 15(c) Confusion matrix of RESNET50

Methodology	Training Accuracy	Validation Accuracy	Test Accuracy
CNN	78.26	73.38	72.71
VGG16	80.42	72.01	74.08
ResNet-50	76.25	65.87	66.44

Fig. 16 Comparision table of Different Methodologies.

Conclusion

This research aims to explore the distinct strengths & weaknesses of prevalent deep learning models for identifying Diabetic Retinopathy at varying stages with acceptable precision. To achieve this, deep learning methods were applied to automatically detect Diabetic Retinopathy using Fundus images of eyes. The basic CNN model served as the foundation, while binary classifiers like VGG16 and RESNET50 were adapted into multi-classifiers. Our findings can assist ophthalmologists in making more accurate and rapid diagnoses. This, in turn, may aid in preventing or managing the disease before it escalates.

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