# Deep Learning and Artificial Intelligence-Based System Architecture for the Classification of Diabetic Retinopathy

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## Abstract:

Diabetics are primarily affected by diabetic retinopathy (DR), a dangerous eye condition that can cause blindness. Blood spills across the retina and erratic blood flow are the results of DR in the retina's blood vessels, which damages the macula. The as retinal tissue swells, vision becomes blurry. Microaneurysms (MAs), which are tiny blood vessel dilatation that resemble little red sacs, are the initial sign of diabetic retinopathy. When DR has advanced to this stage, red dots of various sizes show up on the retina. Third, fluid and proteins from damaged retinal capillaries leak into the eye, forming small, yellowish-white deposits known as exudates (EXs). It could be feasible to avoid irreversible vision loss if DR is identified and treated early. AI is a cutting-edge technology comparable to the Internet and the globalization of electricity. People of all ages can now receive prompt, individualized medical care because to the limitless potential of artificial intelligence and digital image processing technologies. The quick development of medical imaging technology has made a large number of fresh medical images available for research and diagnosis. Medical advancements have been made possible by artificial intelligence.

**Keywords:** Microaneurysm, Exudates, Diabetic Retinopathy (DR), Artificial Intelligence, and Medical Imaging.

## 1. Introduction

Diabetic retinopathy is one of the most debilitating consequences of diabetes. One common and dangerous effect of diabetes mellitus that harms the human eye is blindness.Diabetes mellitus (DM) affects 29 million Americans between the ages of 25 and above. and 74, with diabetic retinopathy affecting 33% of them. An eye condition known as diabetic retinopathy [1][2] is brought on by chronic harm to the retina's blood vessels. Diabetic retinopathies develop through Stages I, II, III, and IV clinically and PDR and NPDR (non-proliferative and proliferative, respectively) pathologically. The mild, moderate, and severe phases of DR's early stages are all described by NPDR. Small red dots form a circular pattern at the end of the blood vessels in the first stage, known as a micro aneurysm (MA); in the second stage, known as a moderate aneurysm, the micro aneurysms develop into deep layers and cause a star-shaped hemorrhage in the retina. Additionally, Severe intraretinal hemorrhages occur in the vein segment linked to well-known intraretinal microvascular anomalies. PDR is the advanced stage of DR, identified by the appearance of new blood vessels as functional microvascular networks within the retina. The four DR phases are graphically represented in Figure 1.

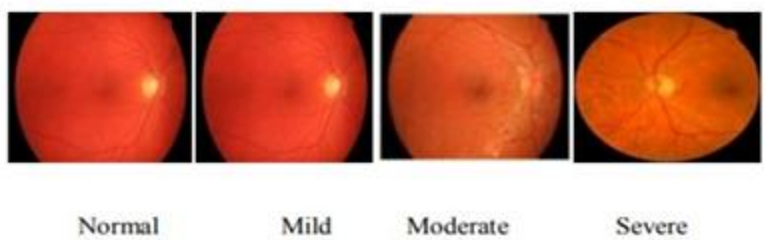


**Figure 1.** Retinal color fundus pictures are used to determine the severity of DR.

## 2. Colour Fundus Photography (CFP)

The fundus, or inner surface of the eye, is composed of the retina, retinal vasculature, optic disc, macular, and posterior pole. A low-power microscope that has been adapted to include a camera for photographing the fundus is called a fundus camera. Eye conditions include macular edema, AMD, diabetic retinopathy, and By scanning the retina, retinal detachment can be identified. One advantage of fundus photography is that it can provide information about our retina that fluorescein angiography would not be able to [3].

## 3. Auto Fluorescence Imaging (AFI)

It is a non-invasive imaging technique that uses naturally occurring fluorescence to show the health of the retinal pigment epithelium (RPE). It is employed to monitor a fundus that is healthy and free of retinal abnormalities. Because AFI has the ability to absorb blue or green light very effectively, blood vessels will appear gloomy. Depending on the measuring device, the optic nerve may appear black due to the absence of RPE in this region [4].

## 4. Fluorescein Angiography (FA)

To get clear images of the retinal blood vessel structures at the rear of the eye, the ophthalmologist may employ angiography. A yellow dye called fluorescein is injected into an eye vein, where it passes through the blood vessels to show any obstructions or fluid leaks. Additionally, it illustrates the a fraction of abnormal blood vessels' ongoing growth [5].

## 5. Optical Coherence Tomography (OCT)

This painless diagnostic method creates a cross-sectional image of the retina using an electromagnetic beam. In order to study the retina, the pupil is enlarged. By detecting the various layers of the retina and determining their thickness, ophthalmologists can utilize this type of tomography to aid in the diagnosis of glaucoma, retinal disorders, age-related macular degeneration, and diabetic eye disease. The various imaging methods now in use are shown in Figure 2[6].

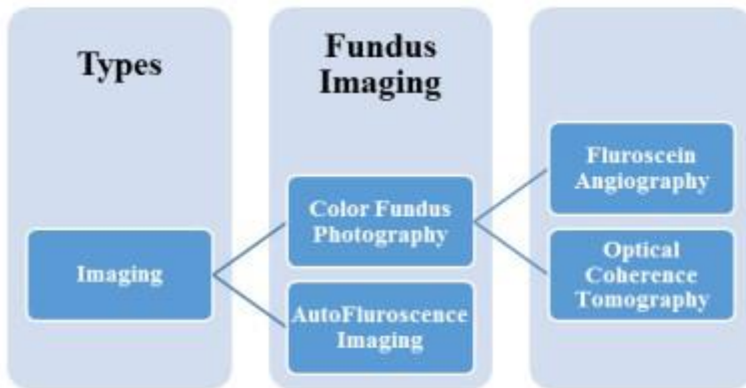


**Figure 2.** Types of Medical Imaging

## 6. Fundus Images

Fundus imaging includes projecting a three-dimensional image of the retina onto an imaging plane. The retina is a semi-opaque, layered tissue covering the back of the eye. According to the National Institute for Clinical Excellence (NICE) in the United Kingdom, a DR screening test should to have a technical failure rate of less than 5% along with a sensitivity and specificity of 80% and 95%, respectively. Early detection of symptoms is typically possible for both diabetic macular edema (DME) and retinal neovascularization.This thorough assessment of the retina was made possible by the detection of DR in fundus pictures [7-9]. Images from cellphones, ultra-wide field cameras, and conventional multiple-field color fundus cameras are included in this study.

**Standard view:** This type of color fundus imaging provides a 30- to 50-degree angle view of the optics and macula. It is commonly used for goals that are pertinent to clinical practice. It is possible to combine various images with a standard 30 degree color fundus image to create a 75 For instance, a horizontal field of vision of one degree. AI algorithms have generally been shown to be capable of accurately identifying DR in color fundus pictures [10].
**Ultra-wide field view:** This type of imaging examines the outermost regions of the retina rather than the central retina and may offer a 200-degree picture of the retina. There is a greater chance of developing DR when the lesions are diagnosed. Given the predictive importance of Peripheral lesions are mostly used in DR screening to predict the onset of advanced illness [11].

**Smartphone-based view:** A smartphone-based decision support system can assist in the screening of DR using the related portable ophthalmoscope. Several factors support the employment of this, such as the high cost of the equipment, the scarcity of skilled eye specialists, as well as the deployment in isolated locations with unidentified patient groups [12][13]. In order to provide affordable options and scalable approaches to widespread treatment, numerous substitutes, such as additional lenses for smartphone cameras, have been developed recently. Potential solutions for the detection of DR are offered by the combination of mobile device-based retinal imaging technology and artificial intelligence models. Figure 3 displays the images of the three views previously stated.

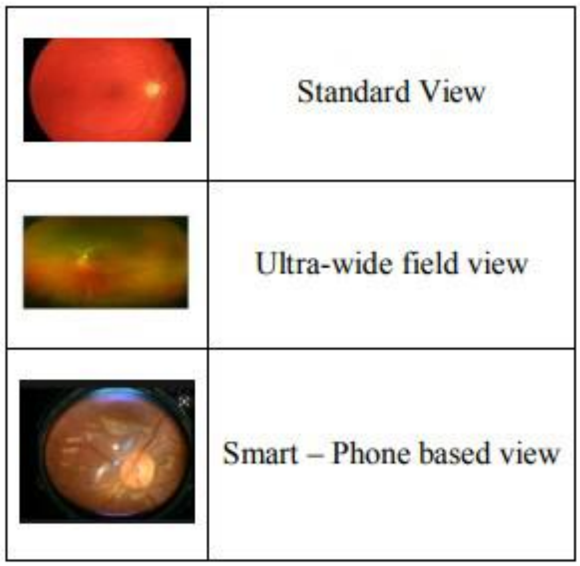


**Figure 3.** Fundus image comparison

## 7. Algorithms for Machine Learning

Large sets of complicated data can have important underlying patterns that can be found using machine learning (ML), a technique for creating prediction models. In studies on ophthalmology, ML methods are often used to correctly identify signs of DR. In terms of retinal abnormalities, it shows that there is a lesion. Random Forest (RF), Support Vector Machine (SVM), Alternating Decision Tree (ADT), Ada boost, Naive Bays, Neural Networks (NN), Logistic Regression, regularized General Linear Model regression (GLMs), and stochastic gradient boosting are among the machine learning algorithms that are available. Precision, Recall, and F1-Score are the performance criteria used to rate these algorithms [14][15]. The machine learning methods are trained using the publicly available dataset that explains the DR's severity grading. The trained model is validated using validation datasets and industry-accepted performance standards. The three main types of machine learning algorithms are supervised, unsupervised, and semi-supervised learning.

## 7.1 Supervised Learning

This kind of learning is used to forecast the output of new, unknown data and relate inputs to outputs. In order to create a prediction model for fresh data, this learning paradigm analyzes the data along with the class labels that correspond to it. Regression and classification are widely used techniques based on supervised education

**Classification:** The process of recognizing and grouping objects is known as classification. When inputs are divided into two or more classes, the classification approach builds a model that allocates unknown inputs to one or more of these classes (multi-label classification). It looks at how comparable data are categorized into groups. Medical image classification is one of the primary techniques employed by Computer-Aided Diagnosis (CAD) systems. Since it provides a wealth of essential information that doctors use to categorize medical images, it is essential to the early detection of disease. A range of deep learning and machine learning approaches are used to develop efficient end-to-end models, which use the raw pixels of medical images to produce final classification labels. High-level properties are extracted in order to classify the medical images [16].

**Regression:**Regression is a statistical method for analyzing the relationships between variables when the outputs are continuous rather than discrete. It is based on supervised learning. Regression in Machine Learning (x) allows data scientists to quantitatively estimate a continuous result (y) based on the value of one or more predictor variables. Considering how straightforward it is in Perhaps the most used kind of regression analysis for forecasting and prediction is linear regression.

## 7.2 Un-supervised Learning

By learning from naive samples, this type of algorithm may automatically identify patterns in the data. It looks for hidden patterns in the information you give it. This type of algorithm examines the data's structure and groups the data into classes according on how similar its components are. A key unsupervised learning strategy is clustering, which divides objects with comparable characteristics into discrete clusters. Every group shares characteristics with other groups that share similar characteristics. Various categories of Things are typically more dissimilar from one another. This is frequently an unsupervised task, as opposed to classification, when the groupings are known beforehand. The capacity to quickly envision Dimensionality reduction enables the discovery of underlying systematic patterns in high-dimensional data.

## 8. Classification of DR Using Regularized Pre-Trained Models

The blood vessels in the retina, which are located in the back of the eye and are light-sensitive, are harmed by diabetic retinopathy, which results in blindness. In the presence of the patient, ophthalmologists and other medical professionals do a thorough dilated eye examination known as fluorescein angiogram in order to identify diabetic retinopathy. Since the current approach is ineffective due to its lengthy duration and resource constraints, alternative approaches are being investigated. Although diabetic retinopathy frequently shows no symptoms at first, it can eventually lead to significant visual loss. This highlights the necessity of automated early diagnosis solutions for DR. Several studies have demonstrated that Deep Learning is the most effective method for correctly classifying medical images. Generally speaking, transfer learning has allowed researchers to correctly classify illnesses by expanding on previously trained models from other domains. It uses the parameters of a system that has already been trained on huge datasets rather than creating whole new CNN architectures for every classification task. This section covers the classification of diabetic retinopathy using several popular pre-trained models, including ResNet50, VGG16, Alex Net, InceptionV3, Mobile Net, Squeeze Net, DenseNet-121, and Xception net.

## 9. Methodology of Regularized XceptionNetArchitecture

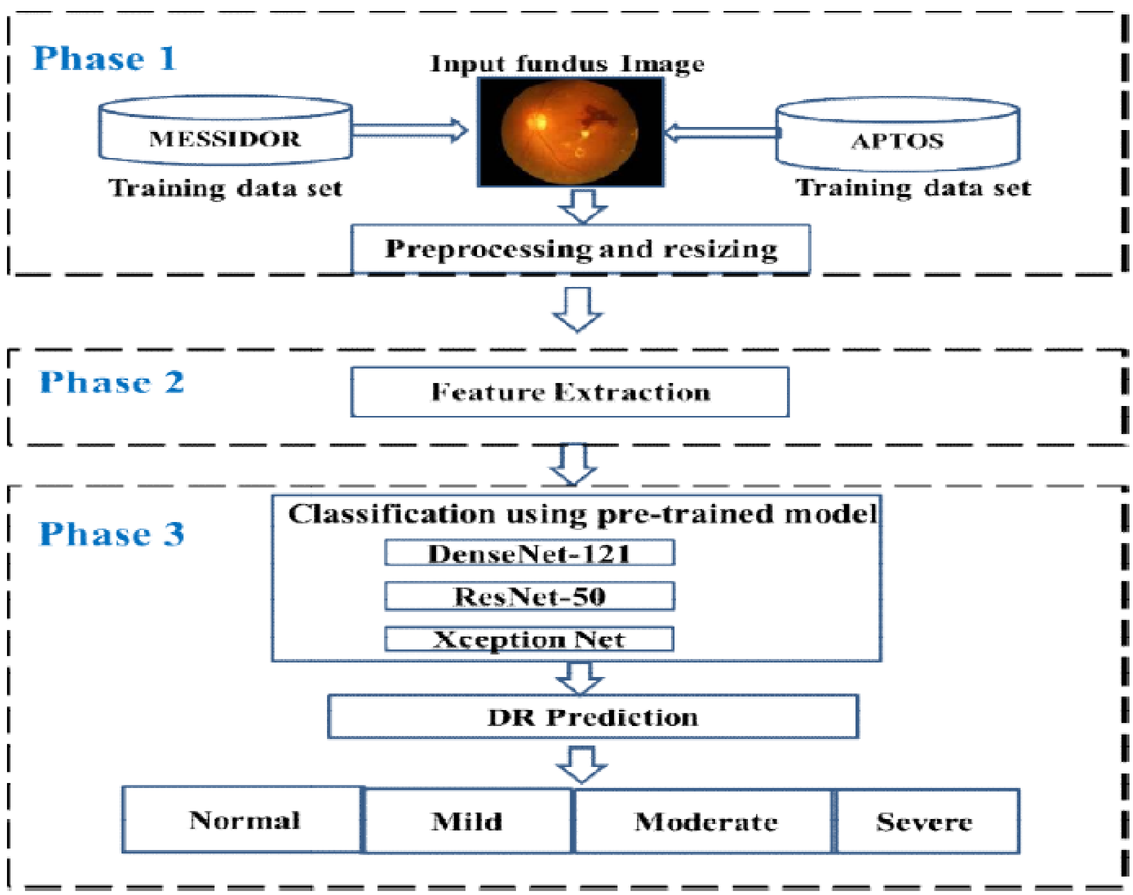


**Figure 4:** Regularized XceptionNet architecture block diagram

Prior to processing the retinal fundus picture dataset as part of the first phase, the goal of this phase is to shrink the dataset. More memory and computations are needed per layer for larger images. The input For the model to perform better and for the training model to pick up the characteristics faster, the images must be scaled. The DR dataset's images are reduced in size at this phase to 224 x 224 x 3 for VGG16, 244 x 244 x 3 for VGG19, 150 x 150 x 3 for Inception v3, 224 x 224 x 3 for Mobile Net V2, ResNet50, DenseNet, and 299 x 299 x 3 for XceptionNet. Extraction of Features the Inception v3 model, which is based on Transfer Learning, is used to extract the features. Blood vessel area, exudates, MA, contrast, homogeneity, correlation, and energy are the characteristics.

## 10.Classification using Pre-Trained Models

### (i) VGG 16

The VGG 16 CNN architecture was created by the University of Oxford's Visual Geometry Group (VGG). Although 224 by 224 pixels is the ideal size for this model, it requires an input picture size of at least 48 by 48 pixels. The dimensions of these filters are 3 by 3. It makes use of filters with sizes between [64, 128 ,256, 512] 13 convolution layers []. There are three thick levels in all, with 4096, 4096, or 1000 nodes in each layer. Every layer utilizes ReLU, the most popular activation function. It makes use of pre-established ImageNet weights trained by ILSVRC.

### (ii) VGG -19

The VGG-19 is a 19-layer convolutional neural network. The network, which has been pre-trained on over a million photos, can be accessed in the ImageNet database. Images can be categorized into one of a thousand categories by the pre-trained network. In VGG-19, a 224x224x3 DR Max pooling layers are used as the handler, and the fundus image is fed into the convolutional layer as the input. Two of the core elements of a CNN are the convolution layer and the ReLU layer. On the other hand, the second cluster is made up of two ReLU layers, a maximum pooling layer, a dropout layer, and a batch normalization layer. Convolutional layers were used to extract features during the training phase, while max pooling layers were used to reduce the dimensionality of the data. VGG19 is used here, and two CNN blocks will subsequently complete the majority of the labor. A flatten layer is used to flatten the data that was taken from the features in the initial classification phase. We employ a dense 512-neuron layer for classification after a dropout layer. The final output of DR can be divided into two categories: healthy and MA images, using a deep layer with four neurons and the SoftMax activation function. There are 22,337,860 parameters in all, including 22,337,604 that may be altered and 256 that cannot. Trainable parameters can and should be different from parameters whose values are set at the start of training altered as the model is improved. Stated otherwise, if the model's parameters cannot be adjusted and optimized during training, then inputs or parameters must be set beforehand. This enables us to create categories while ignoring the untrainable.

### (iii) InceptionV3

Inception V3 is a 42-layer deep learning network with lower parameters. Convolutions are factorized in order to reduce parameters. For example, two 33 convolutions can be used to achieve a 55 filter convolution. By this process, there are just 18 parameters instead of 25. a 28 percent decline. Maintaining a modest number of parameters allows for sufficient precision while lowering the risk of the model becoming overfit.

### (iv) MobileNetV2

The MobileNet architecture uses depth-wise separable convolutions to build compact deep convolutional neural networks. Two global hyper-parameters that enable efficient trade-offs between precision and data storage needs are the width multiplier and the resolution multiplier. It is designed for mobile devices that are more compact and portable. Mobile Net is a deep neural network architecture that consists of 27 convolution layers, an average pooling layer, a fully connected layer that converts the 2-D signal to 1-D, and a final SoftMax output layer.

### (v) Densenet-121

A cutting-edge CNN architecture for category identification and training is DenseNet-121. The name of this structure comes from the 121 interwoven layers and closely spaced architectural elements.The feature maps from the previous layer are used when switching to a new layer. Three are present the design's main structural elements. The main purpose of a dense block is to string its inputs together. A batch normalization layer, a "ReLu" function layer, and a convolution layer make up the convolution block. Due to their strong connection, fewer blocks are lost during training and testing. Figure 5 shows the design of a DenseNet block connection. Notwithstanding the advantages of the DenseNet architecture, the recommended method did not result in appreciable improvements over the current systems. The VGG-16 net model design offers better performance than the DenseNet-121 model.

At 86537.263 seconds, the model executes significantly more slowly than the VGG-16 net model. The DenseNet-121 model uses an image size of 224x224x3 pixels. Table 1 displayed the DenseNet121 hyper-parameters.

**DENSE NET-121**

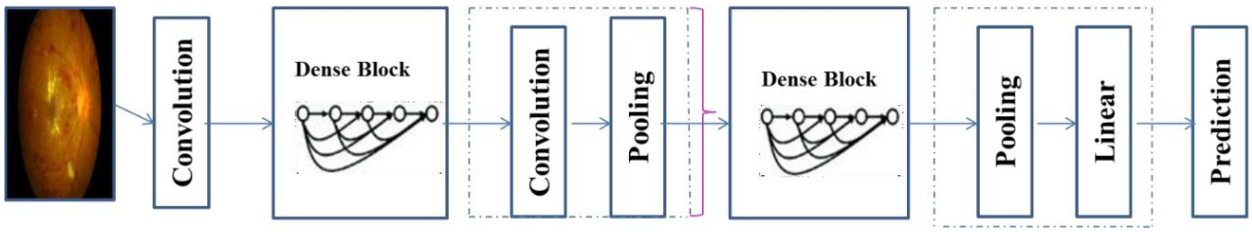


**Figure 5**: Dense Net block connection architecture

**Table 1**: DensNet-121 Hyper-parameters

| Hyper Parameters | DenseNet-121 |
|---|---|
| DropOut | 0.4 |
| ZoomRange | 0.2 |
| Conv2D | 7*7 |
| MaxPool2D | 3*3 |
| AvgPool2D | 2*2 |
| Strides | 2 |
| Padding | same |
| Activation | Softmax |
| Epochs | 100 |
| Dense | 6,12,24,16 |

## 11. Conclusion

Diabetic retinopathy is the leading cause of blindness worldwide, despite the fact that symptoms might not show up until the condition has advanced considerably. Permanent vision loss may be prevented with early DR detection and treatment. If left untreated, it might get really dangerous. As a result, the patient must be screened frequently.to have the ability to promptly identify and resolve issues. In order to help ophthalmologists, improve the retina's appearance, the proposed study sought to automate DR identification. This study's preprocessing strategy and feature extraction approaches, which have been demonstrated to increase classification accuracy, have been focused on identifying red lesions, exudates, and blood vessels in color retinal fundus images. Additionally, the grading process is used to determine the severity of the illness.

## References


1. Pratt, Harry, et al. "Convolutional neural networks for diabetic retinopathy." *Procedia computer science* 90 (2016): 200-205.
2. Ballamudi, VenkataKoteswara Rao. "Utilization of machine learning in a responsible manner in the healthcare sector." *Malaysian Journal of Medical and Biological Research* 3.2 (2016): 117-122.
3. Haloi, Mrinal. "Improved microaneurysm detection using deep neural networks." *arXiv preprint arXiv:1505.04424* (2015).
4. Casanova, Ramon, et al. "Application of random forests methods to diabetic retinopathy classification analyses." *PLOS one* 9.6 (2014): e98587.
5. Li, Baoxin, and Helen K. Li. "Automated analysis of diabetic retinopathy images: principles, recent developments, and emerging trends." *Current diabetes reports* 13 (2013): 453-459.
6. Chandakkar, Parag S., et al. "A machine-learning approach to retrieving diabetic retinopathy images." *Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine*. 2012.
7. Venkatesan, Ragav, et al. "Classification of diabetic retinopathy images using multi-class multiple-instance learning based on color correlogram features." *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2012.
8. Cuadros, Jorge, and George Bresnick. "EyePACS: an adaptable telemedicine system for diabetic retinopathy screening." *Journal of diabetes science and technology* 3.3 (2009): 509-516.
9. OSAREH, AR, and BitaShadgar. "Automatic blood vessel segmentation in color images of retina." (2009): 191-206.
10. Khan, Asifullah, et al. "Machine learning based adaptive watermark decoding in view of anticipated attack." *Pattern Recognition* 41.8 (2008): 2594-2610.

11. Khan, Asifullah, et al. "Machine learning based adaptive watermark decoding in view of anticipated attack." *Pattern Recognition* 41.8 (2008): 2594-2610.
12. Müller, Klaus-Robert, et al. "Machine learning for real-time single-trial EEG-analysis: from brain–computer interfacing to mental state monitoring." *Journal of neuroscience methods* 167.1 (2008): 82-90.
13. Li, Stan Z., et al. "Illumination invariant face recognition using near-infrared images." *IEEE Transactions on pattern analysis and machine intelligence* 29.4 (2007): 627-639.
14. Li, Stan Z., et al. "Illumination invariant face recognition using near-infrared images." *IEEE Transactions on pattern analysis and machine intelligence* 29.4 (2007): 627-639.
15. Saoudi, BaydaaHadi, et al. "MACHINE LEARNING TECHNIQUE FOR DETECTING DIABETES DISEASE." (2006).