Artificial Intelligence and Deep Learning-Based System Design for Diabetic Retinopathy Classification

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Diabetic retinopathy (DR) is a serious eye disease that may lead to blindness and mostly affects diabetics. Damage to the macula is caused by DR in the retina's blood arteries, which leads to irregular blood flow and blood spills across the retina. The retinal tissue expands, making it difficult to see clearly. Diabetic retinopathy manifests first as microaneurysms (MAs), which are small, blood vessel dilations that look like little red sacs. Red dots of varying sizes appear on the retina when DR has progressed to this point. Third, Exudates (EXs) appear as tiny, yellowish-white deposits within the eye due to leaking fluid and proteins from damaged retinal capillaries. If DR is diagnosed and treated before permanent vision loss occurs, it may be possible to prevent it. AI is an innovative technology on par with the Internet and the electrification of the world. Because of the infinite capabilities of artificial intelligence and digital image processing technologies, timely and individualised health treatment is now within reach for people of all ages. An abundance of new medical images are now available for study and diagnosis because to the rapid expansion of medical imaging technologies. Artificial intelligence has made possible new breakthroughs in medicine.

Keywords: Artificial Intelligence, Diabetic Retinopathy (DR), ExudatesMedical imaging, Micro aneurysm .

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1. Introduction

One of the most devastating complications of diabetes is a condition called diabetic retinopathy. Blindness is a frequent and serious consequence of diabetes mellitus that damages the human eye. There are 29 million people in the United States with diabetes mellitus (DM) between the ages of 25 and 74, and among them, 33 percent have diabetic retinopathy. Diabetic retinopathy [1][2] is an eye disease caused by long-term damage to the blood vessels in the retina. Pathologically, diabetic retinopathies go via PDR and NPDR (non-proliferative and proliferative, respectively), and clinically, they progress through Stages I, II, III, and IV. NPDR describes the mild, moderate, and severe stages of DR's early stages. In the first stage, called micro aneurysm (MA), small red dots appear in a circular pattern at the end of the blood vessels; in the second stage, called moderate, the micro aneurysms grow into deep layers and generate a haemorrhage in the retina that resembles a star. Furthermore, serious intraretinal haemorrhages happen in the segment of a certain vein associated with renowned intraretinal micro vascular abnormalities. New blood vessels appear within the retina as functioning micro vascular networks, marking PDR as the advanced stage of DR. Figure 1 shows a graphic representation of the four DR phases.

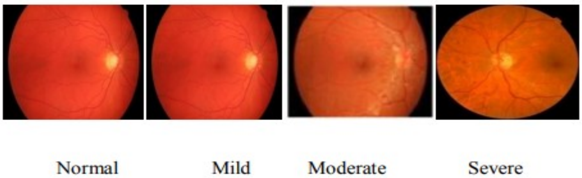

Figure 1. Identification of DR severity from retinal colour fundus images

2. Colour Fundus Photography (CFP)

The retina, retinal vasculature, optic disc, macular, and posterior pole make up the fundus, which is the inner surface of the eye. A fundus camera is a low-power microscope modified with a camera for taking pictures of the fundus. Eye illnesses include diabetic retinopathy, AMD, macular edema, and retinal detachment may all be detected via scanning the retina. Fundus photography has the benefit of revealing details about our retina that a fluorescein angiography would miss[3].

3. Auto Fluorescence Imaging (AFI)

It is a non-invasive imaging method that serves as an indication of RPE (Retinal Pigment Epithelium) health via naturally occurring fluorescence. It is used to track a healthy fundus devoid of any abnormality in the retina. Because AFI may powerfully absorb the blue or green light, blood vessels will seem dark. Due to the lack of RPE in this area, the optic nerve may seem black depending on the measuring tool [4].

4. Fluroescein Angiography (FA)

The ophthalmologist may use angiography to take good photographs of the retinal blood vessel structures at the back of the eye. Fluorescein, a yellow dye, is injected into a vein of the eye and then travels through the blood vessels to reveal any blockages or fluid leaks. It also demonstrates the continued expansion of a subset of aberrant blood vessels[5].

5. Optical Coherence Tomography (OCT)

Using an electromagnetic beam, this painless diagnostic technique produces a cross-sectional picture of the retina. The pupil is widened so that the retina may be examined. Ophthalmologists use this kind of tomography to help in the diagnosis of glaucoma, retinal diseases, age-related macular degeneration, and diabetic eye disease by identifying thedifferent layers of the retina and measuring their thickness. Figure 2 depicts the many imaging techniques now in use[6].

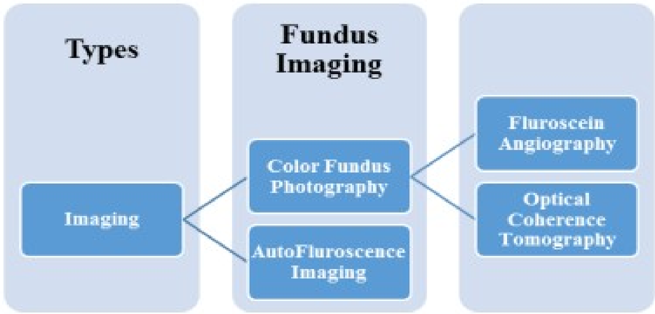

Figure.2. Medical Imaging Types

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. The identification of DR in fundus images allowed for this comprehensive evaluation of the retina[7-9]. This research includes images taken using ultra-wide field cameras, cellphones, and traditional multiple-field colour fundus cameras.

- **Standard view:** This kind of colour fundus photography offers a view of the macula and optics at an angle of 30 to 50 degrees. It is frequently employed for clinically relevant objectives. A conventional 30 degree colour fundus picture may be blended with other photos to provide a 75 degree horizontal field of vision, for example. In general, it has been demonstrated that AI systems can correctly identify DR in colour fundus images[10].

- **Ultra-wide field view:** Ultra-wide field imaging, which may provide a 200-degree view of the retina, investigates the outermost zones of the retina instead of the centre retina. Diagnosis of the lesions is done with a higher risk of DR development. With the prognostic significance of peripheral lesions in predicting the development to advanced illness, it is mostly employed in the screening of DR[11].

- **Smartphone-based view:** The screening of DR with the associated portable ophthalmoscope may be done with the help of a smartphone-based decision support system. The use of this is justified for a variety of reasons, including the expensive cost of the equipment, the dearth of experienced ophthalmic professionals, and the deployment in remote places with undiagnosed patient populations[12][13]. Many alternatives, such extra lenses in smartphone cameras, have been created in recent years to offer cost-effective solutions and scalable ways to broad treatment. Artificial intelligence models combined with retinal imaging technology based on mobile devices provide potential options for the identification of DR. The pictures of the above mentioned three views are shown in Figure 3.

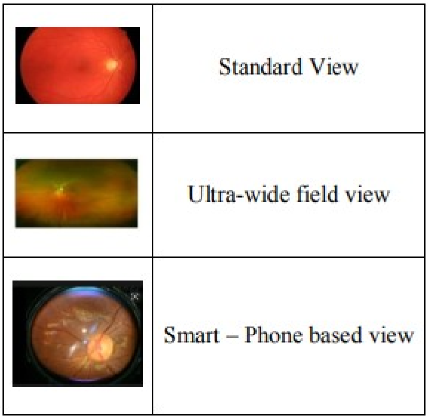

Figure.3 Comparison of fundus images

7. Machine Learning Algorithms

Machine learning (ML) is referred to as a method for building predictive models and is able to identify significant underlying patterns in large collections of complex data. In ophthalmologic research ML approaches are frequently utilized to accurately diagnose DR symptoms. It indicates the presence of a lesion in terms of retinal anomalies. There is a collection of machine learning algorithms available, including Random Forest (RF), Support vector Machine (SVM), Alternating Decision Tree (ADT), Ada boost, Naive Bays, Neural Networks (NN), and Logistic Regression, regularized General Linear Model regression (GLMs) and Stochastic gradient boosting These algorithms are rated based on the performance metrics namely Precision, Recall & F1-Score[14][15]. The publicly accessible dataset that describes the severity grading of the DR is used to train the machine learning algorithms. Utilizing validation datasets and the industry-accepted performance criteria, the trained model is verified. Supervised, Unsupervised, and Semi-supervised learning are the three primary categories of machine learning algorithms.

7.1 Supervised Learning

This type of learning is applied to map inputs to outputs and forecast the output of new unknown data. This learning paradigm works by analysing the data with their associated class labels and builds a prediction model for new data. Classification and Regression are popular technique based on supervised learning

Classification: Classification is the process of identifying and categorizing items. The classification method creates a model that assigns unknown inputs to one or more (multi-label classification) of these classes when inputs are separated into two or more classes. It examines how similar information are classified into classes. One of the main methods used by Computer-Aided Diagnosis (CAD) systems is medical picture categorization. It is crucial to the early diagnosis of disease since it is a rich source of vital data that physicians use to classify medical images. Effective end-to-end models are created using a variety of deep learning and machine learning techniques, and they yield final classification labels from the raw pixels of medical pictures. To categorize the medical pictures, it extracts high-level characteristics[16].

Regression: It is a supervised learning-based technique and it functions as a statistical tool for examining the relationships between variables when the outputs are continuous as opposed to discrete. Data scientists can mathematically estimate a continuous result (y) based on the value of one or more predictor variables using regression in Machine Learning (x). Given its simplicity in predicting and forecasting, Linear Regression is perhaps the most often used type of regression analysis

7.2 Un-supervised Learning

This kind of algorithm is able to figure out data patterns on its own by learning from naive samples. It finds hidden patterns in the data you provide it. This kind of algorithm analyses the structure of the data and sorts it into classes based on the degree to which its elements are similar. Clustering, a crucial unsupervised learning approach, groups items with similar properties into distinct clusters. Each group has features in common with others that have similar attributes. Different groupings of objects tend to be more different to one another. Unlike classification, where the groups are known in advance, this is often an unsupervised task. The ability to easily visualise high-dimensional data and discover underlying systematic patterns in a dataset is made possible by dimensionality reduction.

8. Classification of DR Using Regularized Pre-Trained Models

Diabetic retinopathy causes blindness by damaging the retina's blood vessels, which are positioned in the rear of the eye and are sensitive to light. In order to detect diabetic retinopathy, ophthalmologists and other medical experts undertake a comprehensive dilated eye exam called fluorescein angiography in the presence of the patient. The present method is inefficient since it takes too long and is limited by the available resources; hence other methods are being explored. Diabetic retinopathy often has no early warning signs but may cause severe vision loss over time. This emphasises the need for automated DR early diagnostic solutions. Multiple researchers have shown that deep learning performs best when it comes to accurately categorising medical photos. In most cases, researchers have been able to successfully classify illnesses by using transfer learning to build on pre-trained models from other domains. Instead of building completely new CNN architectures for each classification assignment, it makes use of the parameters of a system that has already been trained on large datasets. This section discusses the use of ResNet50, VGG16, Alex Net, InceptionV3, Mobile Net, Squeeze Net, DenseNet-121, and Xception net, along with other common pre-trained models, to classify Diabetic Retinopathy.

9. Methodology of Regularized XceptionNet Architecture

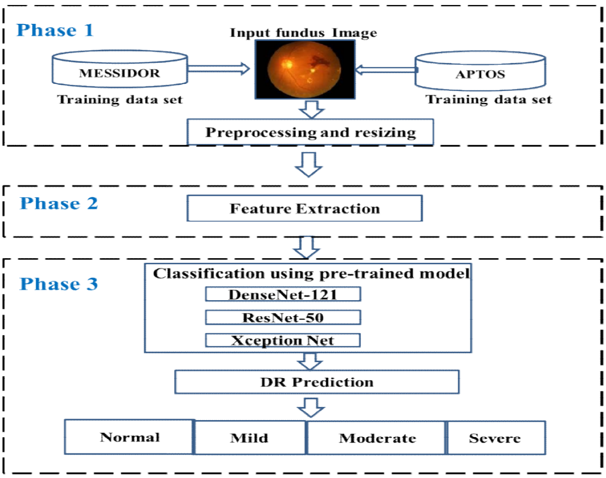

Figure 4 Block Diagram of Regularized XceptionNet architecture

Pre-Processing
The aim of this phase is to resize the dataset before processing the retinal fundus imagedataset as part of the initial phase. Larger images require more memory and calculation processesper layer. The input images must be scaled for the model to function better and for the trainingmodeltolearnthecharacteristicsmore quickly.In this phase, the images of the DR dataset are scaled down to 224×224×3 for VGG16,244×244×3 for VGG19, 150×150×3 for Inception v3, 224×224×3 for Mobile Net V2, ResNet50,DenseNet,and299×299×3forXceptionNet.

Feature Extraction The features are extracted using Transfer Learning based Inception v3 model. The features are area of blood vessels, exudates, MA, contrast, homogeneity, correlation, and energy.

10. Classification using Pre-Trained Models

(i) VGG 16
The Visual Geometry Group (VGG) at the University of Oxford developed the VGG 16 CNN architecture. This model requires an input picture size of at least 48 by 48 pixels, but optimally uses 224 by 224 pixels. These filters are 3 by 3 inches in size. It uses filters with sizes in the range [64, 128, 256, 512] over 13 convolution layers. There are a total of three thick layers, each having a node count of 4096, 4096, or 1000. All of the layers make use of everyone's favourite activation function, ReLU. It uses ILSVRC-trained ImageNet weights that are already set.

(ii) VGG -19
The VGG-19 is a convolutional neural network with 19 layers. The network may be found in the ImageNet database, where it has been pre-trained on more than a million images. The pre-trained network has the ability to classify images into one of a thousand different categories.In VGG-19, a 224x224x3 DR fundus image is sent into the convolutional layer as the input, and Max pooling layers are utilized as the handler.The convolution layer and the ReLU layer are two of the fundamental components of a CNN. The second cluster, in contrast, consists of a maximum pooling layer, a dropout layer, a batch normalization layer, and two ReLU layers. During the training phase, we extracted features using convolutional layers and then employed max pooling layers to minimize the features' dimensionality. Here, we use VGG19, and later on, two CNN blocks will accomplish the bulk of the work. During the first step of classification, the data that was extracted from features is flattened using a flatten layer.Following a dropout layer, we use a dense 512-neuron layer for classification. Through the use of a deep layer with four neurons and the SoftMax activation function, the final output of DR may be classified into two groups: healthy and MA pictures. A total of 22,337,860 parameters are involved, including 256 that cannot be changed and 22,337,604 that can.In contrast to parameters whose values are fixed at the commencement of training, trainable parameters may and should be modified as the model is refined. In other words, inputs or parameters must be set in advance if the model's parameters cannot be modified and optimized during training. This allows us to ignore the untrainable while making categories.

(iii) InceptionV3
Inception V3 is a reduced-parameter 42-layer deep learning network. Parameter reduction is accomplished by factorizing convolutions.A 55 filter convolution, for instance, may be accomplished with only two 33 convolutions. This procedure reduces the number of parameters from 25 to 18, a decrease of 28 percent. Keeping the number of parameters low reduces the likelihood of the model being overfit while yet allowing for enough precision.

(iv) MobileNetV2
In order to create compact deep convolutional neural networks, the MobileNet architecture employs depth-wise separable convolutions. Width multiplier and resolution multiplier, two global hyper parameters, allow for effective trade-offs between precision and data storage requirements. It is tailored for smaller, more portable mobile devices. With 27 convolution layers, an average pooling layer, a fully connected layer to convert the 2-D signal to 1-D, and a final SoftMax output layer, mobile net is a deep neural network architecture.

(v) Densenet-121

DenseNet-121 is a state-of-the-art CNN architecture for both category identification and training. The 121 interconnected layers and densely packed building components that give this structure its name. When moving to a new layer, the feature maps from the previous layer are used. There are three primary structural components to the design. A dense block's primary function is to string together its inputs. The convolution block consists of three layers: a batch normalization layer, a "ReLu" function layer, and a convolution layer. Fewer blocks are lost between training and testing because of how well they are connected. The architecture of a DenseNet block connection is seen in Figure 5 .Despite the benefits of the DenseNet design, the suggested approach did not lead to significant advancements over the existing systems. When compared to the DenseNet-121 model, the VGG-16 net model architecture provides superior performance.

The model takes much longer than the VGG-16 net model to execute, at 86537.263 seconds. The 224x224x3 pixel picture size is used by the DenseNet-121 model.The hyper-parameters for DenseNet-121 were shown in Table 1.

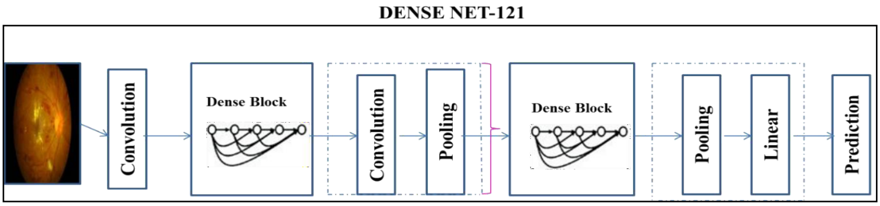

Figure 5: architecture of a DenseNet block connection

Table1 Hyper-parametersforDensNet-121

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

Although symptoms may not appear until diabetic retinopathy has progressed significantly, it is the primary cause of blindness globally. Early detection and treatment of DR may avoid permanent visual loss. It may become quite serious if not handled. Therefore, the patient has to be screened often need to be able to detect and address problems quickly. The suggested research aimed to automate DR detection so that ophthalmologists could better enhance the retina's aesthetics. Detecting red lesions, exudates, and blood vessels in colour retinal fundus pictures has been a focus of this study's pre-processing approach and feature extraction techniques, which have been shown to improve classification accuracy. Furthermore, the grading is done to establish the degree of sickness.

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