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Deep Learning Enabled Diabetic Retinopathy diagnosis using Fundus Images

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Abstract— **One of the primary side effects of diabetes mellitus is diabetic retinopathy. Fundus examination is a frequent method used to obtain retinal pictures for the purpose of assessing the disease's progression. Nevertheless, those pictures might have issues with poor contrast, insufficient illumination, and an excessive amount of noise, among other things that could make medical analysis and action difficult. In this regard, the work seeks to provide low quality digital retinal pictures publicly available in the DDR, EyePACS/Kaggle, and IDRiD databases by applying the neural network VGG16 to classify the diabetic retinopathy in 5 categories and with an additional class (called class 5). Size adequacy pre-processing of retinal images, data cleaning (removing low-quality images from other classes and adding them to class 5), data augmentation and class balancing during the training phase, hyper parameter adjustment, and image classification using the VGG16 neural network are all included in the proposed methodology. This proposal has demonstrated the greatest performance for the DDR database in terms of accuracy, precision, sensitivity, specificity, and F1-score among the tests conducted on the three databases. This work adds performance measures sensitivity, specificity, accuracy, and F1-score, and improves the state-of-the-art results obtained in the DDR and IDRiD databases without DME.**

Keywords— Diabetic Retinopathy (DR), Vgg-16 Model, Retinopathy, Transfer Learning, Retinal Images

I. Introduction

Retinopathy is a major global public health concern. It is a potentially blinding complication of several systemic disorders, including diabetes. Appropriate and prompt identification of retinopathy is essential for successful treatment and preservation of vision. Recent developments in medical imaging, especially in the area of retinal imaging, have made it possible to create automated diagnosis systems. Among these, transfer learning has demonstrated promise in improving the accuracy of retinopathy identification. Transfer learning is a machine learning technique that makes use of pre-trained models on huge datasets for a particular task. Transfer learning makes it possible to adapt complex neural network architectures to the complexities of retinal pictures by utilizing the knowledge gained from a variety of datasets. This ultimately improves the efficiency and accuracy of diagnosing retinopathy. In an attempt to further the continuous efforts to transform early illness identification and enhance patient outcomes, this research investigates the use of transfer learning in the field of retinopathy detection.

II. Materials and Methods

Diabetic Retinopathy is the issues related to public health worldwide. The fifth most prevalent cause of visual impairment worldwide and, consequently, the fourth most common cause of blindness is diabetic retinopathy. The most crucial role health systems play in controlling diabetes and preventing the disease's permanent blindness is collaboration between those in charge of diabetes care and those impacted by diabetic retinopathy. This stage of mild non-proliferative DR (NPDR) is when micro aneurysms develop. The microscopic blood arteries of the retina contain tiny patches of balloon-like inflammation. Moderate NPDR: At this point, the blood vessels supplying the retina are obstructed. Additionally, there are hemorrhages within the retina. Severe NPDR: At this point, more blood vessels are blocked, restricting blood flow to multiple parts of the retina.

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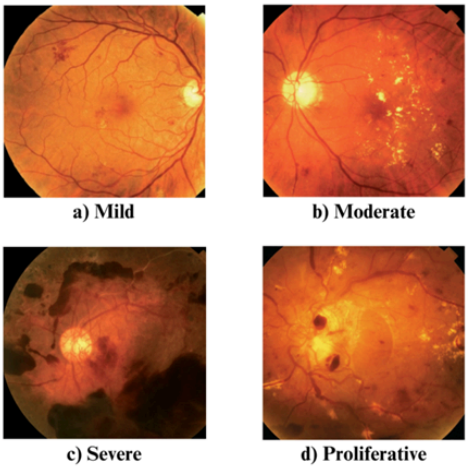

Figure 1. Stages Of Diabetic Retinopathy

There is also a significant increase in the amount of retinal hemorrhage. Proliferative DR: In this advanced stage of DR, new, aberrant blood vessels grow on the surface of the retina. These blood vessels are fragile and prone to bleeding, which can result in vision-threatening hemorrhage filling the eye. Additionally, they will transform into connective tissue, which over time will shrink and separate the retina, leading to blindness. Because every stage has unique traits and qualities, medical professionals could miss some of them and diagnose patients incorrectly as a result. Consequently, the notion of creating an automated DR detection system emerges. Over half of the most recent occurrences of this condition may have been prevented with prompt, efficient treatment and close supervision by eye professionals.

A. VGG – 16 Model

A convolutional neural network (CNN) model is called VGG16. Among the most effective vision model architectures is VGG1-16. On the ImageNet dataset (a collection of 15 million photos in various categories), this model achieves 92.7% top-5 test precision, with 14 million images having a location with 1000 classes. Diverse sets of pooling and convolutional layers make up the VGG-16 architecture. The RGB image of size 224 × 224 serves as the fixed size input for the convolution-1 (convo) layers. The 64 channels of the Convo 1-1 and Convo 1-2 layers have the same padding and are 3 × 3 filter sizes. The receptive field of these filters is extremely narrow. The max pooling layer of stride 2 x 2 comes after the layers of convo1, convo2, and so on. There are two convolution layers (Con2-1 and Convo2-2) again, much like in the prior layers, and a pooling layer comes

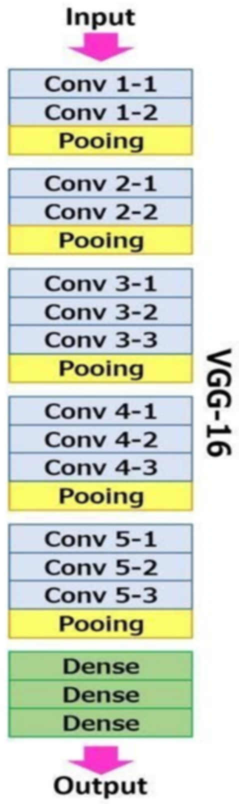

Figure 2. Architecture Of VGG – 16 Model

after. Similar to earlier layers, the convolution-2 layer has a max pooling layer of 2 x 2 strides and a filter size of 256.

B. Transfer Learning

One of the most potent machine learning paradigms, transfer learning, has become a game-changer for improving task performance and efficiency. Fundamentally, transfer learning is the process of using the information that is obtained from solving one problem to another that is connected to it. Transfer learning enables pre-trained models on huge and diverse datasets to be adapted to new tasks, even with insufficient labeled data, in contrast to standard machine learning models that start from scratch. This technology is especially applicable in fields where acquiring large-scale labeled datasets is difficult or costly. Transfer learning has shown incredible promise in the last few years across a wide range of applications, including natural language processing and picture and speech recognition. Transferring learnt features, representations, or knowledge from one domain to another speeds up the learning process and greatly enhances the performance of models on particular tasks, which accounts for its adaptability and efficacy. The foundation for comprehending the function and importance of transfer learning is laid out in this introduction, particularly with regard to its use in the retinal image-based diagnosis of retinopathy.

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C. Retinal Images

Retinal images are detailed pictures of the retina, the innermost layer of the eye, and they provide important windows into eye health. The retina, which is made up of an intricate web of neurons, blood arteries, and light-sensitive cells, is essential to vision. Clinicians can evaluate and diagnose a variety of eye diseases non-invasively by using retinal pictures, which capture the intricate intricacies and anatomical features of this important tissue. These scans offer a multitude of information vital for prompt intervention and treatment, from tracking age-related changes to identifying early indicators of diseases like diabetic retinopathy. Technological developments in medical imaging have improved retinal picture quality and resolution while also creating new opportunities to analyze and interpret these images using AI and machine learning methods. The importance of retinal images grows as we explore the nexus between ophthalmology and technology; they are a vital component of efforts to develop more effective and precise diagnostic methods for a range of ocular disorders.

III. Implementation

Using the VGG16 neural network, a comprehensive method that includes picture pre-processing, data augmentation, class balancing, and hyper parameter tuning is used in the proposed system to identify diabetic retinopathy. Pre-processing identifies low-quality photos for separate classification and guarantees image consistency. While class balancing takes care of the inherent imbalance in the data, data augmentation approaches improve the training dataset. The VGG16 network is optimized for best results through hyper parameter tweaking. The approach performs better than current methods and advances the field of DR classification by successfully classifying retinal pictures into five DR severity levels and identifying low-quality images.

A. Load Dataset

To our knowledge, the Kaggle dataset is the largest collection of fundus photos for diabetic retinopathy, and we used it in our experimental setup. The dataset is arranged by Eye PACS. There are 88,702 photos in the Eye PACS collection; 35126 of those images have labels, while the rest 53,576 do not. We used only the annotated photos from this dataset because our aim, which is a supervised learning problem, is to classify different stages of diabetic retinopathy. In the future, the entire dataset may be used with various semi-supervised learning techniques. DR severity is taken into consideration when distributing the dataset into five different classifications.

B. Data Preprocessing

In order to prepare the data for the model, we resize the photographs while maintaining the aspect ratio of 1349 × 1024. It aids in preventing the loss of features in photos. After then, photos are arbitrarily cropped to a fixed 1024 × 1024 size. Figure 2 illustrates the pre-processing procedures. The distribution of the dataset is 64%, 20%, and 16% for the training, validation, and test sets, respectively. The validation dataset is employed to verify the enhancement of the model at every epoch. As validation loss improves, the learning rate is adopted from 0.01 to 0.0001 in order to prevent over-fitting. Using the Keras Image Data Generator, image augmentation is carried out with a re-scale value of 1/225, shear, and zoom range of 0.2 with real horizontal and vertical flip. During runtime, the data generator automatically adds to the data.

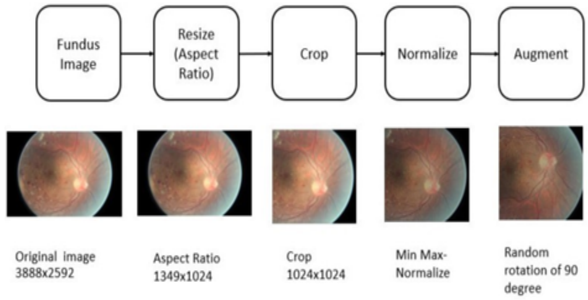

Figure 3. Preprocessing Steps

C. The VGG – 16 Model

An RGB image with dimensions of 224 × 244 is sent into the VGG16. After passing through a block of three fully connected layers, the picture is processed through a sequence of convolutional (conv) layers with filters of 3 × 3 receptive fields. VGG16 network, which computes the features map by performing a number of convolutions and pooling operations. The spatial responses of the receptive fields are preserved by the feature map. Nevertheless, the model is restricted to a limited size input by the VGG16 fully connected layers, which require a fixed-length vector. In both the training and testing stages, the VGG16 requires a fixed size input since it uses completely connected layers. In this instance, the 1024 × 1024 photos in the dataset do not meet the required input size. We must crop or lower the resolution from 1024 × 1024 to 224 × 224 in order to match the VGG16 input size. This reduces the recognition accuracy and causes content loss. In order to do this, we insert a Spatial Pyramid Pooling layer (SPP) between the first completely linked layer and the final convolution layer. Combining the characteristics, the SPP layer generates a fixed-size output vector that satisfies the needs of the neighboring fully linked layer. In summary, the SPP layer performs information aggregation and steers clear of issues that may occur from resolution reduction or cropping.

D. Model Training

The model was trained across thirty epochs. In convolutional neural networks, one loop over the complete training dataset is called an epoch. A neural network often needs many epochs to fully train. The ADAM optimizer was used to train the model. Optimizers are methods or instruments that change your neural network's parameters, including learning rate and weights, in order to reduce losses. Because of its high efficiency and short training

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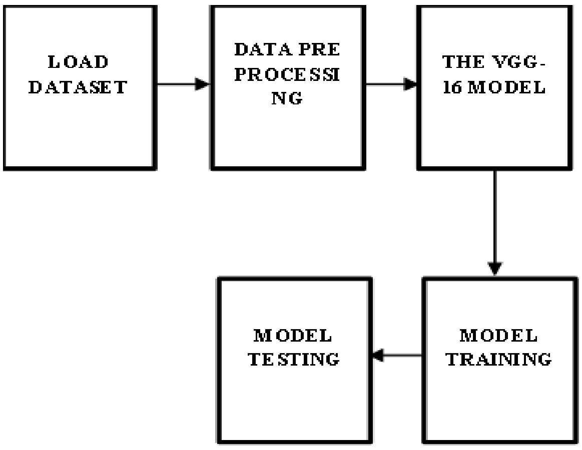
time, ADAM is regarded as the best optimizer. A batch size of 32, a Soft max activated layer, and a Cross Entropy loss function are used to train the model. Adam's default value, a learning rate of 0.001, was employed.

E. Model Testing

Our model was evaluated using a brand-new collection of 1728 retinal pictures, which were not part of the 3668 photos used to train it. Pre-processing and feature extraction are carried out on images while the model is being tested. Using a scale from 0 to 4, the model classifies the output photos based on the severity of diabetic retinopathy. In this sense, our model's accuracy was very good. Over the period of thirty epochs, there was a loss of accuracy. We used Kaggle, an internet-based data science platform, to get the VGG-16 pre-trained model, train, and test our model since it allows users to access and upload datasets and develop projects/models.



IV. Result Analysis

Using the VGG16 neural network, the suggested methodology for classifying diabetic retinopathy performs better, especially when tested on the DDR database. The model demonstrates improved resilience to low-quality photos by virtue of careful data pre-processing, which includes size adequacy and efficient data cleaning. This is demonstrated by the creation of a new class (class 5) dedicated to such cases. The model's good cross-class generalization is facilitated by the training process's integration of data augmentation and class balancing. Hyper parameter tuning improves the VGG16's fit for the job even further.

Type	Precision	Recall	F score	support
Mild	0.83	0.94	0.88	143
Moderate	0.84	0.7	0.77	158
No_DR	0.98	0.98	0.98	149
Proliferate_DR	0.9	0.85	0.87	157
Severe	0.83	0.92	0.87	148

Table 1. Comparison Table

Figure 5. Comparison Graph

A classification model's accuracy, recall, and F1-score metrics are shown for each class. The precision for the 'Mild' class is 0.83, meaning that a big fraction of the real positive cases were captured by the model. The recall is a high 0.94, suggesting that a large proportion of the predicted positive instances are genuinely positive. With 143 instances, the F1-score, which is a harmonic mean of recall and precision, is 0.88, indicating a balanced performance for this class. The precision of 0.84 in the 'Moderate' class indicates a fairly diminished capacity to capture true positives, while the lower recall of 0.7 indicates dependable positive predictions. The 158 cases in this category have an overall moderate performance, as indicated by the F1-score of 0.77. With 149 instances, the 'No_DR' class shows high recall, F1-score, and precision, all at 0.98, demonstrating the model's good performance in recognizing instances of 'No_DR'. Precision is 0.9, recall is 0.85, and F1-score is 0.87 for 'Proliferate_DR,' suggesting that the 157 occurrences exhibit an excellent balance between recall and precision. Finally, the precision, recall, and F1-score for the 'Severe' class are 0.83, 0.92, and 0.87, respectively, demonstrating a great ability to properly identify positive occurrences out of 148 examples. When taken as a whole, these metrics offer a thorough assessment of the model's performance in categorization across several classes.

V. Conclusion

Diabetes is one of the diseases that has grown the quickest in recent years. A diabetic patient has a 30% chance of getting diabetic retinopathy (DR), per several studies. The condition can cause floaters, blurred vision, and finally blindness if it is not identified in its early stages. Manually diagnosing these images takes a lot of time, is difficult, and calls for highly skilled experts. We have effectively created a pre-trained VGG-16 framework that not only identifies diabetic retinopathy but also provides details on the disease's severity.

We succeeded in making the model quite accurate. This approach has the potential to help physicians diagnose this illness more quickly. Analogous models are amenable to development for the diagnosis of different diseases, particularly ocular diseases. This could help prevent lifelong blindness by early detection of these disorders.

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