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A Deep Neural Network-Based Identification System for Diabetic Eye Diseases

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Abstract: Diabetic Eye Disease occurs when blood vessels linked to light-sensitive tissue existing in the retina of the eye are damaged. Furthermore, based on the severity level of the disease, it can lead to full blindness and a variety of other visual problems. The present research work is based on the analysis of various Deep Neural Networks (DNN) that are applied on a dataset consisting of retinal images for the prediction of eye disease especially found in type-2 diabetic patients. This study validates that deep learning-based models such as Visual Geometric Group16 (VGG16), Visual Geometric Group 19 (VGG19), Efficient Network121(EfficientNet121), Residual Neural Network50(ResNet50), and Neural Architecture Search Network Large (NAS Net Large) can predict diabetic eye disease. Several image feature extraction techniques (Contour Feature Description, Segmentation, Color Conversion from BGR to RGB, Gaussian Blur, and Cropping) are used for the feature extraction of color retinal images. The dataset comprised 135930 training images whereas 45310 validation images fitted in five DR types such as No DR, Mild, Moderate, Severe and Proliferative, as a result of data split in ratios of 75% (train) and 25% (test). The accuracy based on training data is compared for all classification models considered in this research work and it has been observed VGG16 gives the highest accuracy. Similarly, the training data accuracy of other models used in this work is also considered (between 85%-99%). Likewise, VGG19 and VGG16 both had high validation data accuracy such as 89.01% and 88.27%, respectively, but ResNet50 had the lowest validation data accuracy of 89.01%.

Keywords: Diabetic Eye Disease, EfficientNet121, NASNetLarge, ResNet50, VGG16, VGG19

I. INTRODUCTION

The prognosis of diabetic eye disease at an initial stage is beneficial for securing eye health of diabetic patients on a wide scale. Although treatment is accessible, many people are expected to lose their vision every day due to this condition [1]. Moreover, it is estimated that around 40% to 45% of diabetic people may have DR at some point in their lives, although the problem swiftly worsens due to a lack of understanding and delayed diagnosis[2].A study presented by the Early Treatment Diabetic Retinopathy Study Research Group(ETDRS) recommends that if the symptoms of this disease are discovered early enough, it can lower the risk of visual loss by half [3]. The frequency of DR is the highest at 25.04%, among adults between the ages of 61 and 80 [4]. The ophthalmologists and physicians used fun do scopic exams to manually examine the retinal images to forecast DR and to identify indicators, such as cotton wool spots, retinal swelling, and other abnormalities but it lacks in accuracy. Therefore, automatic tools are highly required that can analyze the features of retinal images. The present research work is motivated by the availability of diagnostic markers and plenty of features associated with each type of eye disease that can help ophthalmologists to identify retinal changes and differentiate the conditions. The assessment of retinopathy severity necessitates a high level of expertise. Interpretations of the same data set can differ depending on medical expertise, resulting in inaccuracies. Therefore, by applying retinal ophthalmo scopy, clinicians can detect symptoms early and enhance diagnostic efficiency by using deep learning and deep transfer learning techniques to confirm a diagnosisandidentifyessentialtherapies.Thesemethodscanassis tdoctorsinmakinganaccurate diagnosis and identifying lesions[5]. In last decades, the most common applied methods for the classification of diabetic retinopathy are SingleNucleotidePolymorphism(SNP)genotyping,Machinelea rning,andConvolutionalNeuralNetwork (CNN).The accountable portion of the literature is inspired by feature recognition applied in retinal images [6][7]. The objective of the present study is to observe deep transfer learning-based methods that are applicable for the detection of eye disease symptoms in various image formats. Research work is organized as follows: Section 2 comprehensively analyses the literature study, including deep learning architectures and machine learning techniques. The suggested framework and dataset analysis and feature extraction are further described in Section 3. Section 4 illustrates various deep learning architectures have been

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implemented. Section 5 then focuses on the experiments performed and the outcomes obtained us and discuss potential future developments and conclusions

II. LITERATURE SURVEY

Now a day, an automatic detection of diabetic eye disease is an important segment in research field. This section briefly describes various conventional, deep learning as well as deep transfer learning-based methods proposed for the prediction, detection, and labeled classification of diabetic eye disease. The feature-based retinal image analysis system supports flexible grading and monitoring of diabetic retinopathy progression and digital image processing techniques to detect the components of the retinal image to diagnose DR using fund us photography. The estimation of hemorrhage and exudates is used to predict diabetic retinopathy.The Gray Level Co-Occurrence Matrix is calculated with the help

IV. PROPOSED SYSTEM

The proposed method consists of set of phases. As shown in figure 1, first phase included data processing, which consists the preprocessing of datasets. Preprocessing is used to improve the quality of the data by implementing different tasks such as resizing, cropping, noise removal, contrast improvement, data augmentation, etc. However, collecting, visualizing, and transforming data are the important components of th eprocess. In initial stage, identifying missing value, outliers from the dataset, normalization the data and also dealing with feature scaling. In the second stage, data segmentation included which divided the dataset into training and validation sets which included several training techniques and measure the performance of model based on accuracy produced by them. In the present research work, various deep transfer learning models such as EfficientNet121, VGG16, VGG19, ResNet50, and NASNetLarge are used to classify diabetic retinopathy. The detailed discussion of these models have been described in the next section. The performance of the aforementioned models is evaluated and compared it on the basis of various assessment parameters as well as gave insights.Fig.1.:General framework of the diagnostic process for Diabetic Eye Disease Fig. 2:Types of retinal images Dataset Description Dataset considered in the present research work consistsofcolorretinalimagesandaretakenfrom‘Kaggle.’Thesedatasetsrepository is publicly accessible as dataset1[39] and dataset2[40].The dataset used in this paper consists five types of color images. The models are trained using 135930 images and the learning architecture is validated using 45310 images. Retinal images can be classified into Mild, Moderate, Severe, Proliferative, and No DR.The image category mentioned in the study can be seen in the data files with the marked image number.The dataset consists of a big collection of retinal images collected in diverse imaging conditions. There is a left and right field with respect to each subject. The five-grade impairment scale from 0 to 4 are used to mark the DR label as shown in Table 1. The sample image for each DR category is shown in Figure 2above.Table 1: Various DR categories DR Category Impairment No DR0Mild DR1Moderate DR2Severe DR3Proliferate DR4

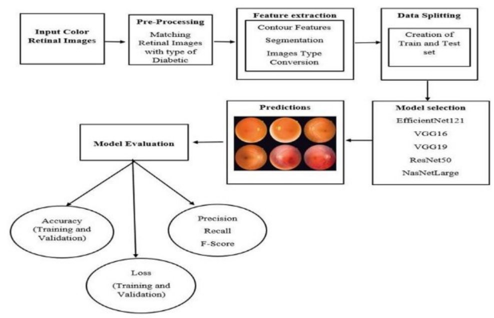

Fig.1. : General framework of the diagnostic process for Diabetic Eye Disease

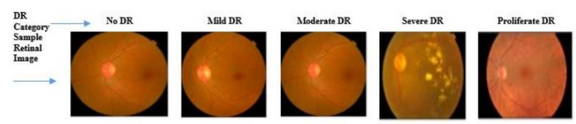

Fig. 2: Types of retinal images

The objective of the research work is to classify retinal images with respect to the type of diabetic retinopathy. The extraction of key features from a retinal image is critical to achieving this goal. The subsequent part of this section describes the morphological and color features to represent such images using the proposed methods. This study has used various methods to extract information from images.3.3.1 Morphological Features(Contour Features) Morphological feature or Contour points are described as anout line that represents the bound the shape of an object.These are continuously defined edges with an identity value and geometrical parameters. These are used to determine object recognition and shape analysis. However, there are several contours’ properties such as Area, Perimeter, Epsilon, Approximation, Width, Height, Aspect Ratio, Extent, Equivalent Diameter, Minimum Value, Maximum Value, Minimum Value Location, Maximum Value Location, Mean Color/ Mean Intensity, Extreme Leftmost Point, Extreme Rightmost Point, Extreme Topmost Point, and Extreme Bottommost Point.3.3.2 Image Segmentation Image segmentation is used for the classification of each pixel in the image through a set of classes that are predefined. Semantic segmentation differs from object detection in that no bounding boxes are predicted around the objects. Different instances with respect to the same object are not distinguished. This section explains the various

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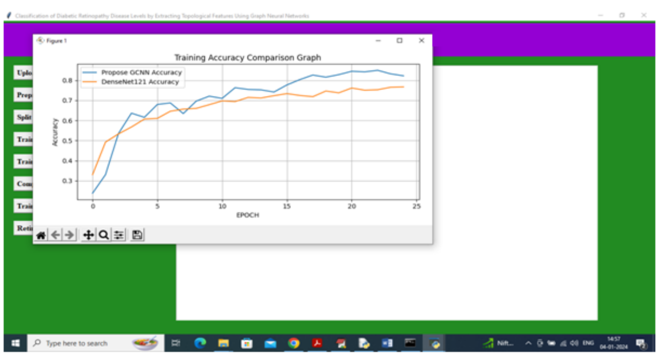
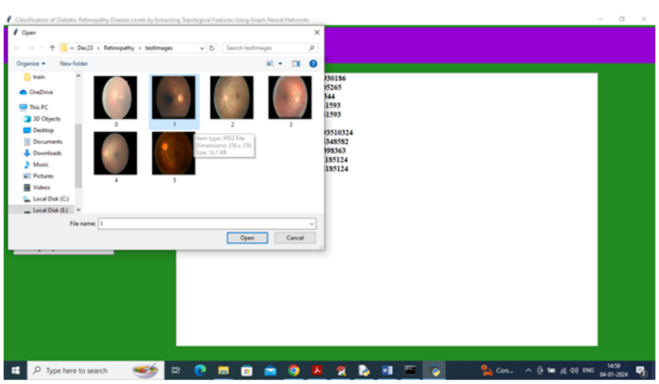
steps, namely, BGR to RGB conversion, Gaussian blur, and cropping applied for image segmentation. The color conversion from BGR (Blue, Green, Red) to the resultant RGB (Red, Green, Blue) is applied for pixel ordering concerning the image processing library used in the present study. RGB color is represented in a structure where blue color is assigned on least significant area. However, second least area is assigned by green color and red color takes up third last position. In BGR the order of areas is reversed. Consequently, red color is assigned to least significant area, green is fixed and blue is in the third last position.Gaussian Bluris a pre-processing operation used to improve the structure of an image. It can reduce the high-frequency components from an image. dissimilar weights. The biggest distinguishing.

V.RESULTS

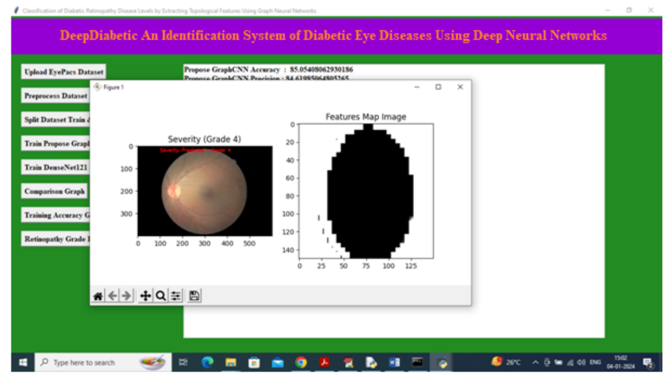
The screenshots of various phases of project are as follows



Screen 1:Accuracy



Screen 2: Predict Diseases



Screen 3 : Predicted Disease

VI.CONCLUSION

The primary objective of the present research work is to analyze various feature extraction methods, image segmentation techniques and measure the performance of five classification models. Consequently, ResNet50, EfficientNet121, VGG16, VGG19, and NASNetLarge models are used for the categorization of color retinal images. The performance of all the models is compared on the basis of various quality metrics such as Accuracy, Root Mean Squared Error, Precision, Recall, and F-Measure and implemented on a dataset of 1,81240 retinal images. Moreover, several feature extraction approaches were used to extract contour features to classify retinal images. Deep learning-based architectures have not only improved the accuracy of existing image recognition and categorization methods but also facilitated several automated learning methods. According to experimental setup, VGG19 achieved a high accuracy level i.e., 99.07% for training dataset and exhibiting deep learning is an appropriate mechanism for retinal image analysis. To improve the prediction rate, the preprocessing steps can be upgraded in the future. In addition, using deep learning-based models, a vast volume of unlabeled retinal imaging data may be analyzed and compared with prior work reported in the classification of diabetic eye disease

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