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Prediction of Diabetic Eye Disease in Type 2 Diabetes Mellitus using Deep Learning based Approaches: A Comprehensive Analysis

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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),EfficientNetwork121(EfficientNet121), Residual Neural Network50(ResNet50), and Neural Architecture Search Network Large (NASNetLarge) 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 whereas45310 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 inthis 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*

1. 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 fundo 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 ophthalmoscopy, clinicians can detect symptoms early and enhance diagnostic efficiency by using deep learning and deep transfer learning techniques to confirm a diagnosis and identify essential therapies. These methods can assist doctors in making anaccurate diagnosis and identifying lesions [5]. In last decades, the most common applied methods for the classification of diabetic retinopathy are Single Nucleotide Polymorphism (SNP) genotyping, Machine learning, and Convolutional Neural Network (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 implemented. Section 5 then focuses on the experiments performed and the outcomes obtained us and discuss potential future developments and conclusions.

2.Literature Review

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

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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 fundus photography. The estimation of hemorrhage and exudates is used to predict diabetic retinopathy. The Gray Level Co-Occurrence Matrix is calculated with the help of various properties like correlation, contrast, entropy, energy, standard deviation, homogeneity, and area, followed by Artificial Neural Network (ANN) classification [8][9], the XGB-Stacking model, based on stacking and XGBoost is also described in the literature.

Although, these techniques reduce redundancy in data and features is decreased and the effectiveness of a single ensemble-based learning classifier is improved [10][11][12], the CNN visualization techniques to distinguish the well-known disorders such as microaneurysms, hemorrhages, exudates, and other ocular components [13] a novel approach named as SVM with Gaussian Kernel for Retinopathy Prediction to train predictive models[14], further a variety of machine learning techniques such as Random Forest, Bagging, Adaptive boosting, and Decision tree are utilized [15][16].

Consequently, the recent advancements in artificial intelligence and image recognition [17], deep learning-based models are prevalent for providing prominent outcomes for several complex tasks such as severity classification of diabetic eye disease [18], brain tumor prediction [19], and many other tasks. A Siamese-like architecture was used to create a new convolutional neural network-based model that can receive two fundus pictures corresponding to two eyes [20], for DR severity identification, Deep CNN with Fuzzy C-Means Clustering has been trained on over a million retinal pictures [21], to categorize color retinal images with high resolution into one of the three severity categories of DR, a large sized Deep CNN with 18 layers and three completely connected layers was implemented [22][23]. A deep learning system based on the collection of three-field or one-field color fundus images is implemented [24] for the prediction of disease.A novel bilinear pooling-based non-homologous network model to classify the diabetic retinal images from the perspective of fine-grained classification is presented [25] [26] that implicated a loss calculation method based on the cross and complementary type of entropy.

A unique stacked architecture-based DL algorithm and image processing schema for removing the unwanted reflectance aspects of the images are used in [27]. Similarly, a deep neural-based composite network architecture having additional gated attention capability for feature description and then spatial pooling is used to get the reduced version of the representations [28]. With the recent advancements in transfer learning models, the outperformers of the Image Net Large Scale Visual Recognition Challenge (ILSVRC) are Google Network (Google Net), VGG, ResNet, Xception, and Inception Residual Neural Network Version 2 (InceptionResNetV2). These methods are exceedingly complicated and computationally costly and are trained on the ImageNet dataset [29] including number of images containing more than 1000 different classes. To implement the severity prediction capability of diabetic retinopathy models, vital work is done to transmit the knowledge garnered by the pre-trained deep CNNs.

A method for extracting relevant features from Singular Value Decomposition (SVD), VGG19, and Principal Component Analysis (PCA) before applying classification is presented in [30]. The NASNet is defined in a nonlinear space through "t-distributed Stochastic Neighbor Embedding (t-SNE) transformation". When compared with these methods in the deep feature space, the study shows that retinal images can be effectively represented through two features in the compact nonlinear space [31]. Descriptors of the convolutional layers of Xception are more effective at expressing retinal images with diabetic retinopathy than those from dense layer descriptors [32]. The combination of features represented by two dissimilar pre-trained networks, like Xception and VGG16, makes a major contribution to retinopathy prediction [33].

Likewise, a deep neural network-based convolution neural network model, VGG19 is trained using the transfer learning method [34], classification of retinal images with three convolutional neural network models: ResNet50, VGG19, and Inception V3 [35] [36], and a general deep learning model based on Synthetic Minority Oversampling Technique (SMOTE) [37] [38] are notable studies. The outcomes of prediction are categorized based on some parameters such as recall, precision, accuracy, area under the curve, recall, sensitivity, specificity, and dice score.

3.Materials and Methods

In this section, dataset and methodologies used in the present research work are briefly described.

3.1 Proposed framework

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 the process. 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.

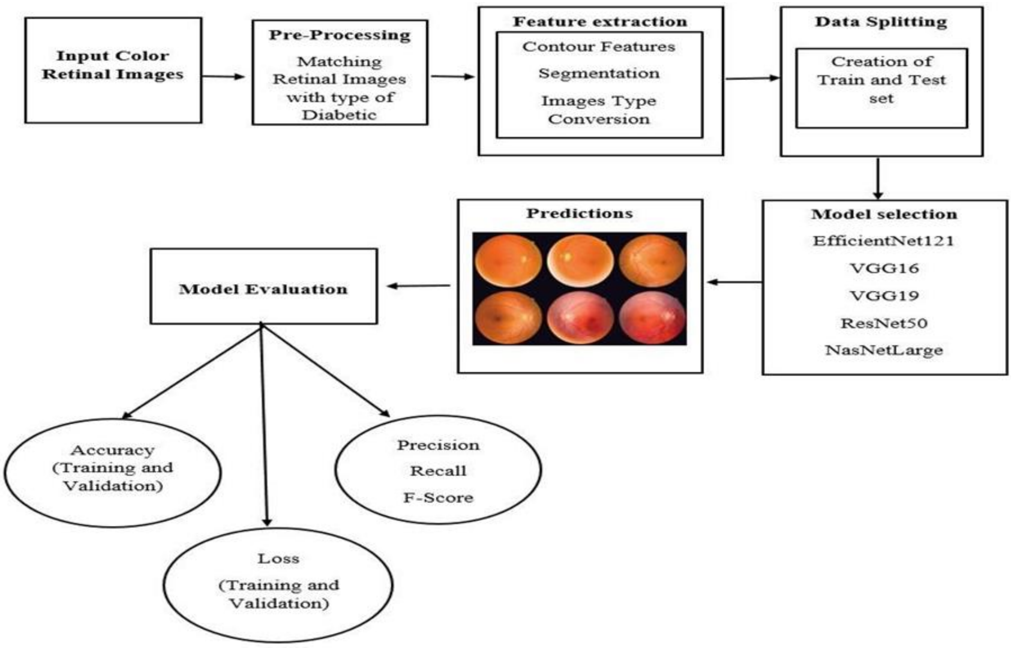


Fig.1. : General framework of the diagnostic process for Diabetic Eye Disease

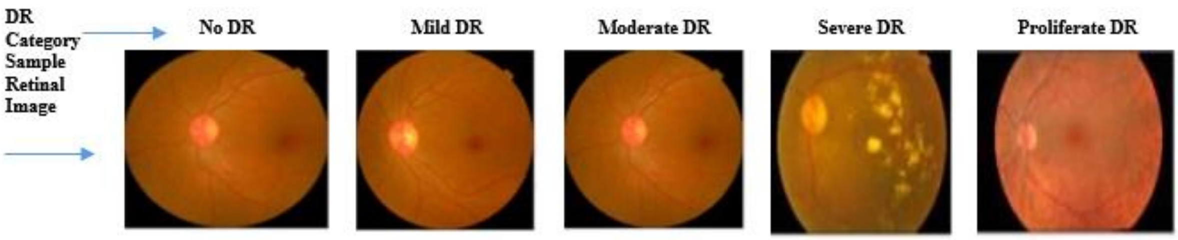


Fig. 2: Types of retinal images

Dataset Description

Dataset considered in the present research work consists of color retinal images and are taken from 'Kaggle.' These datasets repository 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 2 above.

Table 1: Various DR categories

DR Category	Impairment
No DR	0
Mild DR	1
Moderate DR	2
Severe DR	3
Proliferate DR	4

Datasets [39] [40] are captured by using different camera types as well as models. In some images, the retina is shown in its anatomical form. In this form optic nerve is on the right for the right eye whereas the macula is on the left side. Whereas remaining retinas are depicted as these

3.2 Feature Extraction Techniques

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 an outline 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 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 Blur is a pre-processing operation used to improve the structure of an image. It can reduce the high-frequency components from an image. It is a filter for image blurring that calculates the value of transformation through the Gaussian function. The outcome of this operation will produce a smoothly blurred image that is similar to an image as viewed through a translucent screen.

Cropping techniques are commonly used to improve the aesthetic quality of an image by detecting the most salient parts of the image and removing the unwanted content to produce a smaller image that is more visually appealing.By utilizing the semantic information contained in the image, image cropping can also increase the relevance of an image.

3.3.3 Splitting of Dataset

Data splitting is required to ensure model validation. In the present research work, 135930 images have considered for training and 45310 images for validation. The validation dataset is different from the training dataset and it's not included in the model learning. The validation dataset is used for a fair assessment of models.Approximately 75% of the whole data is utilized to train the models whereas the remaining 25% part is utilized for the testing of models.

would appear through a condensing lens on a microscope. In general, the inverted position of the image can be identified in two ways. The first way is, if the image has a mark on one of its sides (circle, square, or triangle), it is not inverted. It is inverted if there is no mark. The second way is, if the macula to some extent is higher than the midline of the optic nerve, it is inverted. It is not inverted if the macula is slightly lower than the midline of the optic nerve .

Deep Learning Models

Deep learning is well known for its use in image categorization. Through the emergence of deep learning, neural networks are applied in a variety of aspects of image categorization. The predictive capability of deep neural networks contributes to the success of neural learning for image categorization [40]. There are five deep transfer models explored in this research work and significance of each model has explained as follows.

EfficientNet121 is a method for designing and scaling convolutional neural networks. It applies a compound coefficient for the scaling of all resolution dimensions, depth, and breadth uniformly. The EfficientNet scaling approach, in contrast to existing practices, uses a predefined set of tuning parameters. EfficientNet adjusts network in a consistent manner to change the resolution, depth, and breadth of the network [41].

ResNet50 is a RestNet variant of a MaxPool layer, an Average Pool layer, and 48 Convolutional layers. To resolve the deterioration problem (i.e., a drop in accuracy as the depth of the neural architecture increases), ResNet uses a technique known as "residual mapping". This technique lets each component layer match the most appropriate mapping rather than just assuming that each stacked level will instantly fit into the underlying primary mapping [42]. ResNets are applicable in diverse kinds of problems. These networks can be optimized as the depth of the network increases, resulting in better results than existing networks.

VGG16 is one of the best vision model architectures. The number 16 in VGG16 signifies this model consists of 16 layers with dissimilar weights. The biggest distinguishing aspect of VGG16 is that it uses 33 filter convolution layers with stride 1, a consistent padding, and a max pool layer of a 22-filter stride 2 .

VGG19 is a variation of the VGG model that includes 19 layers (i.e. 3 Fully connected layers,16 convolution layers, 1 SoftMax layer, and 5 MaxPool layers). VGG19 contains 19.6 billion FLOPs [42].

NASNetLarge is a CNN architecture based on reinforcement learning. The components are not fixed in advance, but a search approach is used to find them. The architecture consists of a combination of reduction cells and convolutional cells. Reduction cells yield a feature map obtained after a two-fold reduction in width and height of the feature map whereas Convolutional cells produce a feature map of the same dimension

4 Experimental Results

4.1 Image quality evaluation parameters

In this paper, a variety of feature sets for retinal image classification are explored. The performance of five classification algorithms namely, EfficientNet121, VGG16, VGG19, ResNet50, and NASNetLarge, is measured in terms of accuracy, loss and Root Mean Square Error (RMSE). The weighted loss and accuracy are used to assess the prediction model performance in a systematic manner. Based on the training and validation data, all obtained scores are then divided into two groups. The experimentation for this research work is carried out with a NVIDIA GEFORCE RTX 2080Ti GPU of 8 GB capacity. CPU is intel CORE i3 processor ,2.1 GHz. The operating system for training models is windows 11. The Keras, Tensorflow, Imultis, Pandas, Matplotlib, Seaborn, Sklearn, CV2 are the libraries used. However, Matplotlib is open source and freeware tool that is used to visualize charts and graphs. Pandas library is also used to manipulate the data. Moreover, dataset is also imported by Pandas library.

4.1.1 Accuracy

Accuracy is an evaluation parameter that is commonly used to quantify and explain the algorithm's performance. The accuracy of a model is normally calculated once the parameters of the model are expressed and specified in percentage. It is a metric that shows how accurately a model's performance contrasts with the actual model. The Eq. 3 shows the accuracy metric.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \qquad (3)$$

Where TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative respectively.

4.1.2 Loss

A loss value that is lower indicates a more accurate model. The loss value is calculated and interpreted for the training as well as validation datasets. Loss is the count of all inaccuracies made in each occurrence of training and testing sets. Loss is not represented in percentage like accuracy.

4.1.3 Root Mean Square Error (RMSE)

For the comparison of observed and expected values, RMSE is a regularly used in statistic. The calculated deviations are called 'Prediction Errors' if computed out of the sample and 'Residuals' is calculated based on the sample data chosen for estimation. RMSE is used to integrate the scales of different data point prediction mistakes into a single predictive power estimate. The value of RMSE is always positive and a zero value denotes that the data has been perfectly fit. In most circumstances, a smaller value of RMSE is appreciable rather than a higher value. The Eq. 4 represent the RMSE:

$$\text{RMSE} = \sqrt{\frac{\Sigma(\hat{Y}_t - Y_t)^2}{n}} \qquad (4)$$

Where $\hat{Y}_t$ represents the projected value, Y_t is the actual observed value, and n is the observation count.

4.1.4 Precision

Precision is a quality metric that quantifies the number of correct positive predictions made. To determine the precision value, Eq. (5) is mentioned below:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (5)$$

4.1.5 Recall

Recall is a quality metric that quantifies the number of correct positive predictions made from all positive predictions that could have been made. To determine the recall value, Eq. (5) is mentioned below:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (6)$$

4.1.6 F1-Score

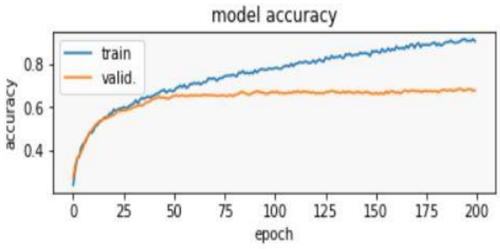
F1-score is the harmonic mean of precision and recall. It combines precision and recall into a single number using the following Eq. 7:

$$\text{F1-Score} = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \qquad (7)$$

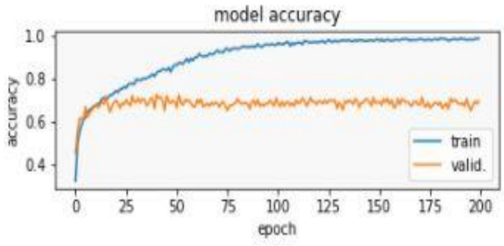
4.2 Performance Evaluation

In this section, the performance of EfficientNet121, VGG16, VGG19, ResNet50, and NASNetLarge is measured in terms of accuracy, loss, RMSE, precision, recall and F1-Score. Figure 3 illustrated an accuracy curve of the deep learning-based models explored in the present research work. Line plots displaying the learning curves for accuracy of multiple learning architectures using training and testing data across each of the epochs are also shown in Figure 3. According to Figure 3, training accuracy is more consistent, whereas the validation accuracy is inconsistent.

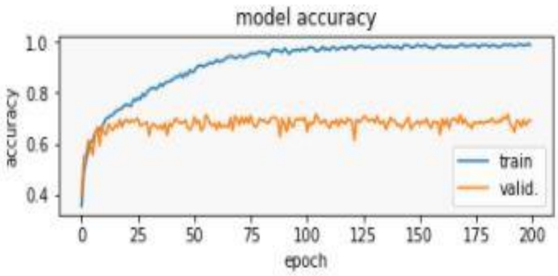
After 125 epochs, the training accuracy of VGG16, VGG19, and ResNet50 becomes stable and exceeds 98% accuracy. After 175 epochs, the training accuracy curve for EfficientNet121 and NASNetLarge becomes practically steady. Only EfficientNet121 and NASNetLarge show smaller volatility with validation accuracy. After 10 epochs, the training and validation accuracy of EfficientNet121 and NASNetLarge is stable, indicating improved prediction-based performance.



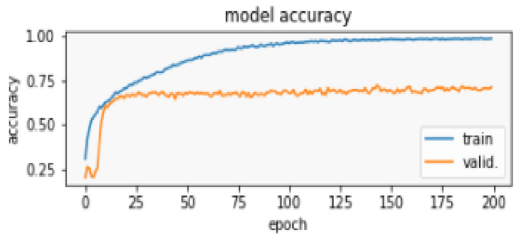
(a) EfficientNet121



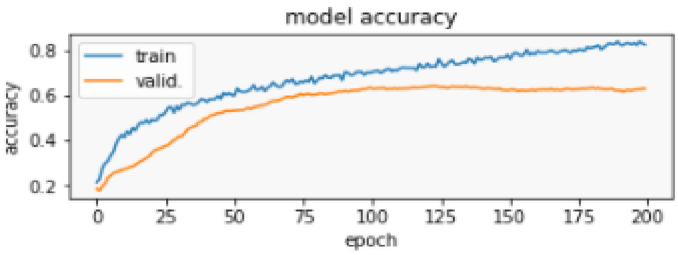
(b)VGG16



(c) VGG19



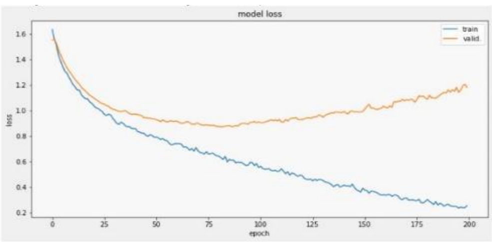
(d) ResNet50



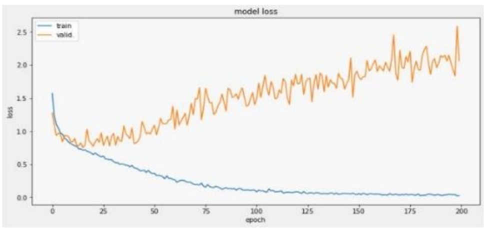
(e) NASNetLarge

Fig. 3: Accuracy Curves of the five prediction algorithms

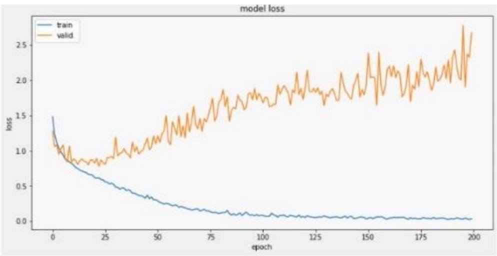
Figure 4 depicts the loss curve of five predicting underlying learning model. Line plots demonstrating loss sustained by several deep learning models on train and test data over each of the epochs. According to Figure 3**,** the deep learning models lost less on training data than on validation data. The trainingloss decreased gradually in all learning models, but the validation data revealed frequent volatility and substantial losses. In terms of training data, VGG16, VGG19, and ResNet50 have suffered the least loss, whereas validation data has suffered the most loss.



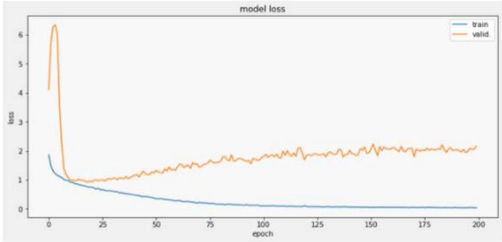
(a) EfficientNet121



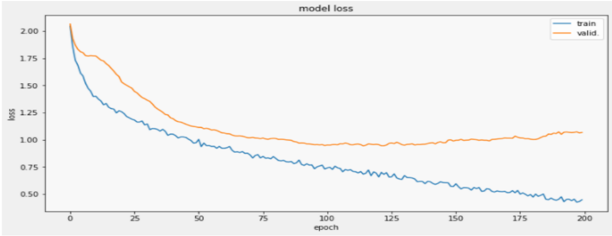
(b) VGG16



(c) VGG19



(d) ResNet50



(e)NASNetLarge

Fig. 4: Loss Curves of the five prediction algorithms

4.3 Average accuracy loss and RMSE

The training and validation accuracy, loss, and RMSE values of the five classification models are illustrated in Table 2. According to Table 2, all models considered for present research work have shown higher accuracy on the training dataset than on the validation dataset. Similarly, models using for training data have less loss as well as RMSE values than models with the validation dataset. When comparing models based on training accuracy score, the VGG16 outperforms with accuracy 99.07%. In terms of training data, however, all classification models perform admirably (>85%). In the case of validation accuracy, VGG19 and VGG16 have the best results (> 88 %), whereas EfficientNet121 hasthe least accurate results. Considering loss and RMSE, all classification models performed well on training data,but their prediction losses and RMSE rapidly increased on the validation sets. As a result, it can be inferred that, in terms of prediction outcomes, the VGG16 model performed the best. The highest classifier assessment score for each parameter is represented by bold values.

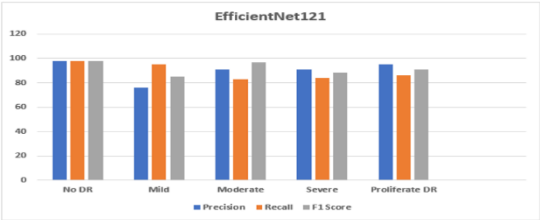
Table 2: Training and Validation results of five prediction algorithms

Algorithms	Training Results			Validation Results		
	Accuracy	**Loss**	**RMSE**	**Accuracy**	**Loss**	**RMSE**
EfficientNet121 [39]	90.93	0.24	0.489898	78.15	1.14	1.067708
VGG16 [40]	**99.07**	**0.02**	**0.141421**	88.27	1.58	1.256981
VGG19 [42]	98.70	0.03	0.173205	**89.01**	1.67	1.292285
ResNet50 [40]	98.55	0.03	0.173205	81.23	1.16	1.077033
NasNetLarge [42]	85.42	0.44	0.663325	83.11	**1.06**	**1.029563**

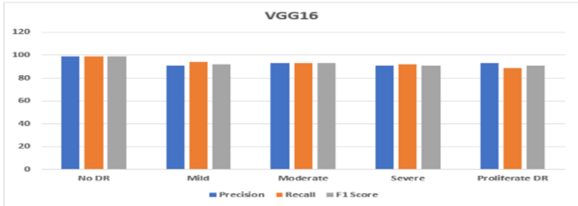
4.4 Comparison of the prediction performance

In this Section, a comparison of prediction performance of five categories of diabetic retinopathy with the help of five deep learning algorithms is shown in Figure 5**.** The prediction performance is compared in terms of Precision, Recall and F1-score and the equation corresponding to each metric is mentioned in Eq. 5,6 and 7 respectively. The range of F1-Score lies between 0 to 1. The EfficientNet121 architecture has predicted the 'No DR' categorywith 98% accuracy, precision, and recall. ResNet50 predicted Proliferative DR with 0.96 precision, 0.89 recall, and 0.92

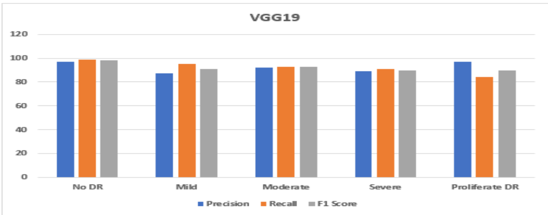
F1 score. VGG16 predicted three categories, Mild DR, Moderate DR, and Severe DR with the highest accuracy and precision.



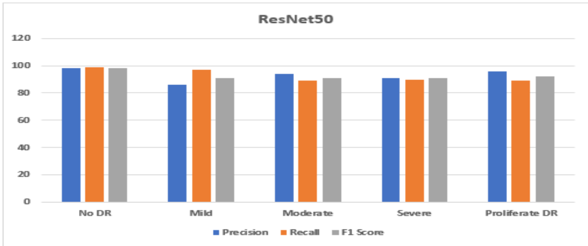
(a) EfficientNet121



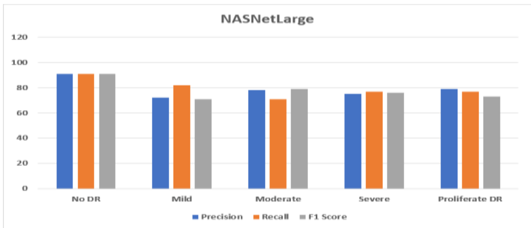
(b) VGG16



(c)VGG19



(d) ResNet50



(e) NASNetLarge

Fig. 5: Performance of the five prediction algorithms

4.5 Overall Performance

Deep transfer learning is used in the present study on a significant amount of data. The primary goal of the studyis to predict and categorize the kind of diabetic retinopathy in retinal images. Five deep learning-based classification models namely, EfficientNet121, VGG16, VGG19, ResNet50, and NASNetLarge are explored in the present study. Several feature extraction and segmentation techniques are used to extract features from retinal images. The objective of the study is to categorize retinal images extracted from five categories of DR. According to the quality metrics, VGG16 performances better in terms of accuracy (99.07%), loss (0.02) and RMSE (0.141421) as compared to all other deep learning models (EfficientNet121, VGG19, ResNet50, and NASNetLarge) used for eye disease severity classification. This study employed a dataset of 1,81,240 files used for image classification from five different DR categories.

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.

Author contributions

Pawandeep Sharma: Conceptualization, Methodology, Data curation, Writing-Original draft preparation,

Amanpreet Kaur: Writing- Reviewing and Editing.

Conflict of interest No conflict of interest.

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