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Enhanced model to detection of Diabetic Retinopathy using Deep Learning techniques

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ABSTRACT

Diagnosing and treating diabetic retinopathy (DR) early on can prevent vision loss. None, moderate, mild, proliferate, and severe are the top five DR phases. This work presents a deep learning (DL) model that identifies all five stages of DR more accurately than earlier approaches. the suggested method with image enhancement using a contrast limited adaptive histogram equalization (CLAHE) filtering algorithm in conjunction with an enhanced super-resolution generative adversarial network (ESRGAN), and circular mask with using random search for hyperparameter. The next step was using augmentation techniques to create a balanced dataset using the same parameters for both scenarios. The created model outperformed previous techniques for identifying the five stages of DR, with an accuracy of 90% , using Efficient net B3 applied to the Asia Pacific TeleOphthalmology Society (APTOS) datasets.

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Main text

The goal of this paper is to build fully automated, scalable, and computationally efficient methods for DR diagnosis based on deep learning, namely Convolutional Neural Networks (CNN). In order to identify the most suitable network for our study, we looked at the pretrained CNN architecture efficient net B3 after they were changed to appropriately represent DR diagnosis in its five stages.In this study, we investigate the impact of hyperparameter tuning on the training of convolutional neural networks, specifically focusing on the EfficientNet-B3 architecture. We present two approaches to model training: one utilizing a random search algorithm to optimize the learning rate hyperparameter and the other employing a fixed learning rate.

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1. Introduction

Mellitus causes the degenerative eye disease DR, which is a direct outcome. People with diabetes mellitus experience persistent blood glucose increases when the pancreas does not produce or release enough blood adrenaline [1,2]. The majority of diabetics develop DR, particularly those in low-income countries who are of retirement age. For chronic diseases like diabetes to have minimal negative effects, early detection is essential [3,4].

The defining feature of DR is irregularities in the retinal vasculature, which can develop into irreversible visual loss as a result of scarring or bleeding [1,5]. As a result, there could be a gradual loss of eyesight and, in the most extreme case, blindness. Since there is no known cure for the condition, treatment concentrates on maintaining the patient's current level of vision [6,7]. If DR is identified and treated right away, a patient's sight can typically be spared. An ophthalmologist must manually examine retinal pictures in order to diagnose DR, which is an expensive and time-consuming technique [8]. In order to diagnose DR, the majority of ophthalmologists still employ the time-tested technique of examining retinal images for the existence and nature of various abnormalities[9,10]. The four most frequent types of lesions were microaneurysms (MIA), hemorrhages (HEM), soft exudates (SOX), and hard exudates (HEX). which can be identified as the following:

- Because of a weakening in the artery walls, MA manifest as tiny, red spots on the retina in early DR. The dots are at least 125 m in size and have clear edges. Microaneurysms come in six different kinds, although all of them can be treated the same way [10,11].

- Unlike MA, HM are characterized by large spots with unequal edge widths of more than 125 m on the retina. Depending on whether the spots are on the tissue's surface or deeper within it, a hemorrhage can either be flame- or blot-shaped [12,13].

- Soft exudates, also known as SX, are caused by the swelling of nerve fibers and manifest on the retina as white ovals.

- Plasma leaking causes EX, or yellow patches on the retina. They have distinct edges and spread over the retina's outermost layer [1,2].

- While the blemishes brought on by the two types of exudates tend to be bright, lesions brought on by MA and HM typically have a reddish hue. Figure 1 illustrates the five main stages of DR that can be identified: no DR, mild DR, moderate DR, severe DR, and proliferative DR [14].

- Experts in the field are required to undertake DR diagnosis manually, despite the fact that even the most skilled ophthalmologists have difficulties as a result of DR variability. These flaws can be identified using precise machine learning methods for automatic DR detection [2,8].

- Our goal was to create a rapid, fully automated DL-based DR categorization that could be applied in the real world to help ophthalmologists evaluate DR. If DR is quickly identified and treated after it first manifests, it can be avoided. To accomplish this, we trained a model on the publicly accessible APTOS dataset [15,16] utilizing cutting-edge picture preprocessing methods and an EfficientNetB3 [17] model for diagnosis.

Related Work

This section presents a review of the most recent Deep learning techniques that researchers applied their interest and solutions for the DR detection, table. 1.

R.Ghosh et al(2017). suggested With color fundus retinal photography as the input, a Convolutional Neural Networks (CNNs) strategy is suggested to automate the procedure of detecting diabetic retinopathy (DR). Our network employs CNN and denoising to spot characteristics on the retina such micro-aneurysms and hemorrhages.

Theano, an open-source Python tool for numerical computation, was used to create their models. Using a powerful GPU and the Kaggle dataset that is freely available, we trained this network. Their suggested model performs with around 95% accuracy for the two class classification on the data set of over 30,000 images and with approximately 85% accuracy for the five class classification in approximately 3,000 validation images[18]

S.Dutta et al (2018) the proposed model has been trained with three types: back propagation NN, Deep Neural Network (DNN), and Convolutional Neural Network (CNN). Deep learning models are outperforming NN. Testing models using CPU-trained neural networks, which have one hidden layer and the lowest accuracy .The FUNDUS pictures data set that we used. Due to CNN's CPU training time being affected in the study, both CNN and DNN models are effective in terms of images [19].

T. Shanthi and R.S. Sabeenian's suggested model uses convolutional neural networks with appropriate Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers. Using the Messidor database, the suggested algorithm's performance has been verified. Classification accuracies of 96.6%, 96.2%, 95.6%, and 96.6% have been attained for healthy pictures, and images of stages 1, 2, and 3 of diabetic retinopathy [20].

In their innovative CNN design, M. Shaban et al. (2020) [21] updated the visual geometry group 19 (VGG-19) by adding two convolutional layers and a recurrent learning unit to the middle two stages, resulting in an architecture with 18 convolutional layers and three fully connected layers. The parameters of the suggested model were initially set using the VGG-19 pre-trained weight. The DR phases were divided into three categories by this model: normal, moderate (which included mild or moderate DR patients), and severe (which included severe NPDR or PDR). Using a class-specific augmentation technique, the model was enhanced before being tested on the APTOS2019 dataset. Image pre-processing, which could boost performance, wasn't used in the researcher's investigation.

S. H. Kassani et al.'s modified Xception was presented in 2019[22] by concatenating features taken from the intermediary layers. In order to train the model and enable accurate classification of DR into five stages, a multilayer perceptron holds onto the extracted information. To demonstrate the effectiveness of their upgraded network, the researchers evaluated it against the first-generation Xception, ResNet50, and InceptionV3.

Resizing, main-pooling filter, normalization, L1 and L2 regularization procedures are just a few of the pre-processing methods used.

The newest Kaggle competition was APTOS2019 fundus pictures dataset.

According to Q. Nguyen et al (2020), introduced an automated classification system that uses machine learning models to classify the severity of diabetic retinopathy (DR) based on the analysis of fundus images with various lighting and fields of view VGG-16, VGG-19, and CNN. This method successfully classifies pictures into 5 categories ranging from 0 to 4, where 0 is no DR and 4 is proliferative DR, with 80% sensitivity, 82% accuracy, 82% specificity, and 0.904 AUC.[23].

S. Mishra et al(2020) .'s recommended that (the project) focuses on the analysis of several DR stages. As a result, they are using the deep learning architecture "DenseNet" A library of over 3662 train pictures was used by 121Architecture to automatically determine the DR stage. These photos are separated into high-quality images of the fundus. The name of the used dataset is available on Kaggle (APTOS). The DR process involves five steps. The numerals are 0 through 4. images of the patient's cornea are used as input criteria. modeling programs (DenseNet) Architecture will continue to extract the fundus picture characteristics. of an eye, after which the activation function provides the output. With this design, DR detection has an accuracy of 0.9611 (quadratic weighted kappa score of 0.8981). And ultimately, they are contrasting the VGG16 and the two CNN architectures accuracy values are 0.7326 and 0.9611 for architecture and DenseNet121 architecture, respectively [24].

The work of M. R. Islam (2020)[25] was concentrated on picture pre-processing using a novel image smoothing method (Gaussian filter). The researchers added two fully connected layers to the pre-trained VGG-16 model and then used it with pre-trained weights while relying on TL. Additionally, the diagnosis job in this study involves five DR phases and was conducted using the APTOS2019 dataset. By paying close attention to image pre-processing, the researchers were able to demonstrate the proposed approach's high accuracy, although the research simply relied on accuracy to assess the model's performance.

Additional criteria, such sensitivity and specificity, which are crucial in the medical industry, were not derived.G . Mushtaq et al proposal .'s from 2021, The Densely Connected Convolutional Network DenseNet-169 is used in the current work to examine a deep learning approaches for diabetic retinopathy early diagnosis. According to their severity levels, the fundus pictures are categorized as No DR, Mild, Moderate, Severe, and Proliferative DR. The datasets used are Aptos 2019 Blindness Detection and Diabetic Retinopathy Detection 2015, both of which were obtained from Kaggle. The data collection preprocessing, augmentation, and modeling processes make up the suggested technique. their suggested model was 90% accurate. The accuracy of the Regression model, which was also used, was 78%. When compared to other SVM, DT, and KNN are examples of machine learning classifiers, the suggested method performs the best [26].

C. Lam, et al investigated multi-nomial classification models and showed that mistakes mainly arise in the categorization of mild disease as normal because the CNNs are unable to recognize subtle disease signs . They found that contrast-based preprocessing constrained adaptive histogram equalization and enhanced the recognition of subtle traits maintaining dataset fidelity through expert class label verification. Peak test set accuracies on 2-ary, 3-ary, and 4-are classification models were increased to 74.5%, 68.8%, and 57.2%, respectively, using transfer learning with ImageNet's pre-trained GoogleNet and AlexNet models [27].

Kumar Gangwar and et al, they discuss the issue of automatic diabetic retinopathy identification, and provides an unique deep learning hybrid to resolve the issue. They add a bespoke block of CNN layers on top of the pre-trained Inception-ResNet-v2 and utilize transfer learning on that to build the hybrid model. APTOS 2019 blindness detection and the Messidor-1 dataset for diabetic retinopathy were used to assess the performance of the suggested approach (Kaggle dataset). Compared to other published results, this model performed better. On the Messidor-1 and APTOS datasets, they obtained test accuracy results of 72.33% and 82.18%, respectively [28].

G. Ghan and et al, suggested methodology uses a Regional Convolutional Neural Network (R-CNN) approach to diagnose DR from digital images of anatomical structures. R-CNN 93%, SVM 85.6%, and KNN 55.17% are used to evaluate the proposed method's accuracy with SVM and KNN classifiers for DR classification [29].

W. L. Alyoubi et al. (2021)[30] created CNN512 and CNN299, two CNN models for automatically detecting DR phases. The researcher creates CNN models from scratch for each model, using various numbers for the Conv, max-pooling, BN, and FC layers as well as one zero padding. The input images were (512 x 512 x 3), and (299 x 299 x 3). In this study, the previously trained EfficientNetB model was also examined. The contrast of the fundus images was improved by using the CLAHE and Gaussian filter to minimize noise. This study also included data augmentation, color standardization, and cropping. The models were assessed using the APTOS2019 dataset obtaining an accuracy of 89%.

Four CNN models were utilized by Oulhadj et al. [31], including DenseNet-121, Xception, InceptionV3, and ResNet50. The Kaggle APTOS dataset's retinal pictures were registered, and the CNN models were used to score diabetic retinopathy. The findings showed that 85.28% was the greatest accuracy level attained.

Table 1 - ***Methods review of DR detection using Deep Learning techniques***

Authors& years	Dataset	Proposed techniques	Accuracy
R.Ghosh et al 2017	EyePacs	CNN	95%
S. Dutta et al 2018	FUNDUS Kaggle	BNN, Deep Neural Network (DNN), and Convolutional Neural Network (CNN). Deep learning models	BNN 42% ,DNN 86.3% , CNN 78.3%
Shanthi and R.S. Sabeenian **2019**	Messidor database	Convolutional neural networks with appropriate Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers	96.6%
S. H. Kassani et al. 2019	APTOS 2019	Xception	83.09%
M. Shaban et al., 2020	APTOS 2019	Proposed CNN (18Conv+3FC) Layers, VGG-19 modified version where 2 Conv layer Proposed CNN (18Conv+3FC) Layers, VGG-19 modified version where 2 Conv layer	88%-89%,
Q. Nguyen **2020**	EyePACSdataset from Kaggle	Using machine learning models such as CNN, VGG-16 and VGG-19.	82%
S, Mishra et al **2020**	Kaggle (APTOS).	Using the deep learning architecture "DenseNet"	% 0.96
M. R. Islam et al., 2020	APTOS 2019 Blindness Diagnosis	Convolutional neural networks (CNN)VGG16 freeze layers + 2 FC layers	% 0.91
G. Mushtaq et al **2021**	Aptos 2019 Blindand 2015 from Kaggle	Densely Connected Convolutional Network DenseNet-169	90%
C. Lam, et al **2021**	Rapid Kaggle	CNN GoogLeNet and AlexNet models	increased to 74.5%, 68.8%, and 57.2%,
A.Kumar Gangwar,et al 2021	APTOS 2019 blindness detection and the Messidor-1	CNN ResNet-v2	72.33%
G.Ghan and et al 2021	IDRiD	Regional Convolutional Neural Network R-CNN	93%
W. L. Alyoubi 2021	APTOS 2019	Proposed CNN512 model (zero padding, 6 (Conv, Max Pooling) , 8 BN, 2 FC, and SoftMax layer)	89%
Oulhadj et al. 2022	Kaggle APTOS	DenseNet-121, Xception, InceptionV3, ResNet-50	85.28%

3. Data Set Description

It is essential to choose a dataset with a sufficient number of excellent pictures. The APTOS 2019 (Asia Pacific Tele-Ophthalmology Society) Blindness Detection Dataset , a freely accessible Kaggle dataset with a substantial number of images, was used in this investigation. High-resolution retinal images are shown for each of the five stages of DR in this collection, which are rated from 0 (none) to 4 (proliferate DR), with labels 1-4 denoting the four severity levels. As shown in Table 2, there are 3662 retinal images in total, of which 1805 belong to the "no DR" group, 370 to the "mild DR" group, 999 to the "moderate DR" group, 193 to the "severe DR" group, and 295 to the "proliferate DR" group. The dimension of the images is 3216 × 2136 pixels, and Figure 1 contains some samples of this type of image. Like any real-world data set, the images and labels contain some background noise. It's likely that the photographs you receive will have some sort of imperfection, such artifacts, blurriness, bad exposure, or another problem. The photographs were gathered over a considerable amount of time from numerous various clinics using various cameras, all of which contribute to the overall high degree of diversity[15,32].

Table 2. Class-Wide Image Distribution.

Class Index	DR Level	# Images
0	No DR	1805
1	Mild DR	370
2	Moderate DR	999
3	Severe DR	193
4	Proliferate DR	295

4. Proposed Methodology

The dataset used to create the automatic DR classification model is shown in Figure 1 along with a general breakdown of how it worked. It shows two distinct cases: case 1 and case 2, in which the preprocessing step is carried out using CLAHE, followed by ESRGAN, and circular mask and conducted, along with augmentation of the pictures to prevent overfitting in both cases. Last but not least, case 1 of the Efficient net B3 model used random search during the classification step, while instance 2 did not.

4.1 Preprocessing Using CLAHE and ESRGAN

It is common practice to collect images of the retinal fundus utilizing a variety of facilities and technology. Consequently, it was essential to improve the quality of DR images and remove different kinds of noise due to the significant intensity variation in the photographs used by the suggested method. Prior to augmentation, case 1's photos all underwent a preliminary preprocessing phase, and training required a number of steps, including:

1.CLAHE

2. ESRGAN

3. image masking

4. Resize each picture to 400 _ 400 _ 3 pixels.

By redistributing the input image's brightness values, CLAHE was utilized to enhance the DR image's small features, textures, and low contrast [29]. The input image was initially divided into four tiny tiles using CLAHE.

Four processes, including computation, excess calculation, distribution, redistribution, and scaling and mapping using a cumulative distribution function (CDF), were used to histogram equalize each tile with a clip limit. A histogram was produced for each tile, and bin values over the clip limit were combined and spread across other bins. In order to convert tile values to CDF values, histogram values were first generated using CDF for the input image's pixel scale. Bilinear interpolation joined the tiles to increase contrast [30].

This method enhanced local contrast enhancement and enhanced the visibility of boundaries and slopes. Figure 3 shows how ESRGAN was applied afterward to the results of the step before. Sharp edges in ESRGAN [33] photographs can be more accurately imitated [3,35]. photos were normalized so that their intensities were within the range of 1 to 1, because the intensity discrepancies between photos can be quite substantial. This reduced noise and kept the data within acceptable limits. A circular mask is a sort of filter used in image processing to emphasize or modify specific circularly shaped parts of a picture. It is essentially a binary mask where the circular region of interest is represented as ones (white) and the remainder of the image is represented as zeros (black).[36]

4.2 . Data Augmentatio

Before train the model to the dataset images, data augmentation was applied to the training set to enhance the amount of images and address the imbalanced dataset issue. When given more data to learn from, deeper learning models typically perform better. By making various alterations to each image, we may benefit from the characteristics of DR photos. Any modifications to the input image, such as zooming in or out, flipping it horizontally or vertically, or rotating it by a specific number of degrees, have no effect on a deep neural network (DNN). Through the use of data augmentations, data are structured, overfitting is minimised, and imbalances in the data set are rectified. In order to solve the imbalance problem, we used data augmentation, which entails creating more copies.

4.3 Learning Model (Efficient net B3)

To improve the performance of an EfficientNetB3 model designed for classification tasks on a given dataset, we used a random search method made possible by the Keras Tuner package. The first step of the procedure is to load the class labels and the associated image data into memory. The images are then scaled down to 224x224 pixels and converted to NumPy arrays. Categorical class labels, ranging from 0 to 4, are converted into a one-hot encoded format to aid in categorization. After that, the dataset is split into training and testing sets, with 20% of the data set set aside for testing.

The Keras Tuner search space is established by initializing a Random Search tuner from Keras Tuner. This step involves defining the model-building function, optimizing for validation accuracy, and configuring various parameters, such as the number of optimization trials and the storage directory for results,then initiates a search for the optimal hyperparameters. It calls upon the tuner's "search" method, executing a random exploration of the specified hyperparameter space. Multiple model configurations are trained and evaluated, with the best-performing model, determined based on validation accuracy, being saved.The best-discovered hyperparameters are extracted for future reference. A fresh model, incorporating these optimal hyperparameters, is created. Subsequently, this model undergoes training on the training data for 10 epochs.

5. Experimental Results

PyCharm is used for development and evaluation of the proposed system. It is implemented on the 64-bit Windows 11 Pro OS. Additionally, Python 3.11.2 was used in conjunction with NumPy, Keras, Matplotlib, OpenCV, and Keras Tuner as external support libraries.

TensorFlow 2.7.0, an open-source Deep Learning toolkit, was chosen for this study primarily because it has a Python API, a ton of documentation, and a sizable community where the library is regularly updated. It is simple to set up and use.we split dataset into 80% for training and 20% for validation and testing . All photographs were reduced in size during the training process to 224 × 224 × 3 pixel resolution. We use random search hyperparameter (learning rate) three values which using (0.1 0.001 ,0.0001) Each time one of these values is tested before training , the best value that gives the best results is chosen by random search for use it during training.

6. Evaluative Parameters

The evaluation procedures and their findings are covered in this section. Classifier accuracy (Acc) is a metric used to gauge performance. Equation (1) calculates it by dividing the total number of examples in the dataset by the number of instances (pictures) that were properly classified. The precision (Prec) and recall (Re) of picture categorization systems are frequently assessed. Equation (2) shows that precision increases as the number of perfectly labeled images increases, whereas recall is the proportion of correctly categorized images in the dataset to those that are numerically linked (3). The more accurate the system is at forecasting the future, the better its F1 score. Equation (4), (F1sc), can be utilized to calculate the F1-score. It was discovered that the greatest probability responses from model N should correspond with the anticipated softmax distribution with regard to the study's final criterion, top N accuracy. If at least one of N predictions matches the target label, the classification is accurate.

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \qquad (1)$$

$$Recall = \frac{TP}{TP+FN} \qquad (2)$$

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

$$F-score = 2 * \frac{Recall*precision}{Recall+precision} \qquad (4)$$

True positives, represented by the symbol (T p), are successfully anticipated positive cases, and true negatives (T n) are effectively predicted negative scenarios. False positives (F p) are falsely predicted positive situations, whereas false negatives (F n) are falsely projected negative situations.

7. ***Performance of efficient net B3 Model Outcomes***

The pre-trained Efficient net B3 model's performance on two datasets was investigated in the experiments for this approach. On the (APTOS 2019) dataset, this technique had an accuracy of (90%) when using random search while without it , achieved accuracy (84%)

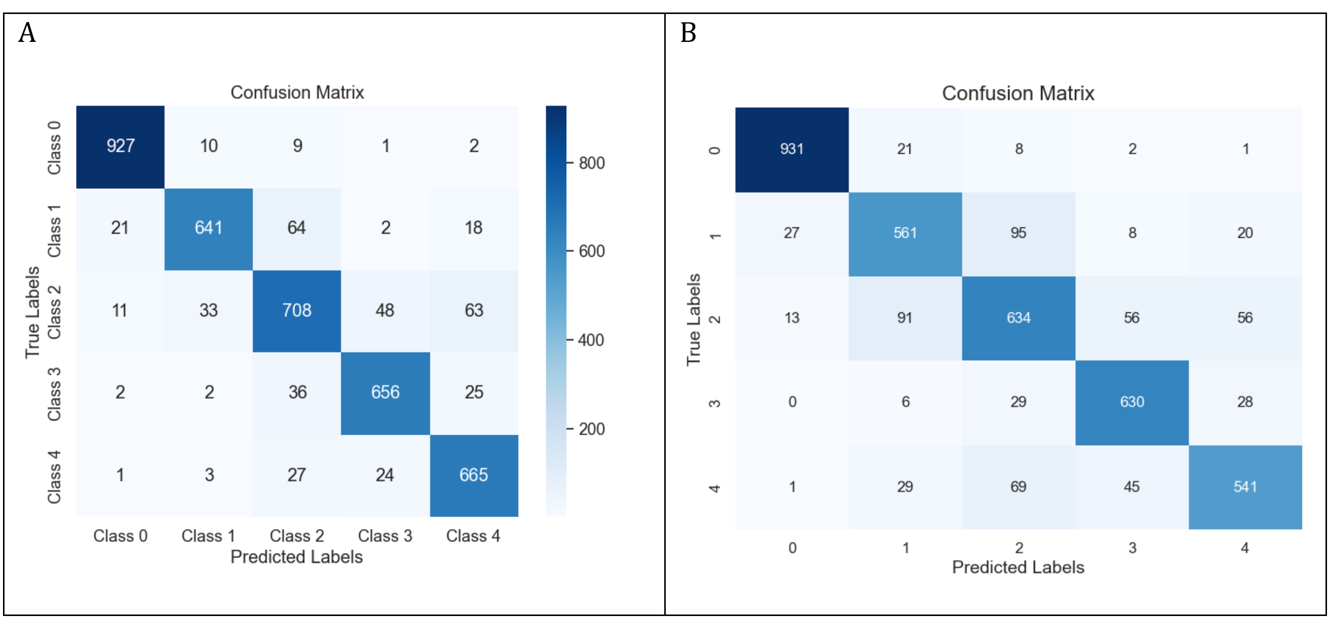

Figure (2) Confusion Matrix of proposed CNN model on APTOS 2019 dataset in A , and B without random search.

Table (3) The performance metric for all strategies

	Datasets			
	APTOS 2019			
Performance metric	**Accuracy**(%)	**Recall**	**F1-score**(%)	**Precision** (%)
Efficient net B3 with using random search	90 %	90	90	90
Efficient net B3	84	84	84	84

8. Evaluation Considering a Variety of Other Methodologies

Effectiveness was compared to that of other methods. According to Table 4, our method exceeds other alternatives in terms of effectiveness and performance . The proposed inception model achieved an overall accuracy rate of 90 %, surpassing the present methods.

table 4. Comparison of system performance to previous research using the APTOS Dataset.

Technique	**Years**	**Authors**	**Dataset**	**Accuracy**
Transfer learning EfficientNet-B3	2021	A.Sugeno , et al [36]"	APTOS 2019	0.84
CNN ResNet-v2	2021	A.Kumar Gangwar,et al [28] 2021.	APTOS 2019	72.33%
EfficientNetB3	2022	Praveen B, et al [38]	APTOS 2019	75.68%
Our proposed model (Efficient Net B3 with using random search)	2023	-	APTOS 2019	90%

9. conclusions

in this paper We developed a method for rapidly and precisely diagnosing five different types of cancer by identifying retinal pictures shown in the APTOS dataset. The suggested The method uses CLAHE and ESRGAN-enhanced photos , noise is removed and the luminance of the image is increased using four-stage picture enhancement procedures. Experimental results showed that the two stages having the greatest influence on accuracy were CLAHE and ESRGAN.

Modern methods for training an effective net B3 with augmentation techniques on preprocessed medical imaging helped to lessen overfitting and increase the overall competencies of the suggested methodology. This answer demonstrated that the conception model, while applying Efficient net B3, attained a correctness of 90% which are comparable to the accuracy of experienced ophthalmologists.

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