An Efficient System for Identification of Eye Disease in Fundus Images using a Deep Transfer Learning-based Pre-trained Model

Himanshu Sharma
Computer Science & Engineering Department, Mangalayatan University, Uttar Pradesh, India
sharma_himanshu86@rediffmail.com (corresponding author)

Javed Wasim
Department of Computer Engineering and Applications, Mangalayatan University, Uttar Pradesh, India
javed.wasim@mangalayatan.edu.in

Pankaj Sharma
Computer Science & Engineering Department, Eshan College of Engineering, Mathura, India
topankajsharma126@gmail.com

Received: 16 July 2024 | Revised: 30 July 2024 | Accepted: 11 August 2024

 DOI: https://doi.org/10.48084/etasr.8408

ABSTRACT

Ophthalmologists rely heavily on retinal fundus imaging to diagnose retinal diseases. Early detection can enhance the likelihood of a cure and also prevent blindness. Retinal fundus images can be used by medical professionals to diagnose retinal conditions such as diabetic retinopathy and retinitis pigmentosa. This study proposes an automated diagnostic approach using a Deep Learning (DL) model to identify fundus images with a high prediction rate. This study aims to use multilabel classification to identify diseases in fundus images. An EfficientNet-B5-based model was trained on a fundus image dataset to classify images as normal, NPDR, and PDR. Image preprocessing was used, including conversion to RGB format, resizing to 224×224, and image filtering using the Gaussian blur algorithm. Additionally, 10-fold cross-validation was used to train and validate the proposed approach. The enhanced EfficientNet-B5 model demonstrated superior validation and training accuracy for eye disease classification compared to existing techniques, achieving 96.04% and 99.54%, respectively. This technology enables early detection and treatment of eye conditions, potentially improving patient outcomes.

Keywords-vision; eye diseases; fundus images; deep learning; TL; image preprocessing; EfficientNetB5

I. INTRODUCTION

When insulin production drops below normal levels or the body is unable to properly metabolize the insulin it generates, a chronic and systemic disease known as diabetes develops. Over time, diabetes affects the circulatory system, particularly the retinal circulation. Diabetes Retinopathy (DR) is a pathological disorder characterized by retinal damage resulting from fluid leakage from blood vessels to the retina. This eye condition is more prevalent in those with diabetes and is a major contributor to vision loss. Approximately 415 million people diagnosed with diabetes are susceptible to developing blindness [1, 2]. Among the numerous forms of retinal diseases, there are, for example, Glaucoma (GLC), AMD, and DR [3-5]. The identification and monitoring of ophthalmologic disorders are highly dependent on ocular fundus imaging. Due to the lack of ophthalmologists, specialized technology, and medical services, the number of patients is growing rapidly. An automated approach may reduce this burden. DL techniques have recently been used to automatically diagnose eye diseases, showing great diagnostic sensitivity and specificity [6, 7]. Transfer learning is also used to extract features and detect eye diseases [8, 9].

DNNs with several layers and filters are used to determine and differentiate between different aspects of fundus images to diagnose eye diseases. Misdiagnosis or failure to identify a disease can occur when the fundus image is damaged by pixels that are too dark or too light or by imperfections in the lighting that are not smooth or uniform. Therefore, image quality is an important feature of fundus images and a necessary first step in classifying them. In [10, 11], quality assessment was not integrated to remove low-quality images before diagnosing eye diseases. As a result, the topic of integrated quality evaluation in the context of multiclass fundus image classification is novel in this investigation. The fundamental objective of this study is to examine whether transfer learning methods can effectively

detect DR, a serious fundus disease, in healthy eyes. Before feeding images to a neural network, this study applies image preprocessing algorithms. Transfer learning methods apply the acquired features from training on fundus images to facilitate classification. This study makes a substantial contribution by outperforming current methods and presenting a comprehensive resolution for the precise classification of eye disorders in fundus images. The contributions of this work are:

- In light of disease classification in fundus images, this study employs deep learning techniques in combination with the EfficientNet-B5 architecture.
- This study employs the DDR dataset, with a specific emphasis on three distinct classes: normal, NPDR, and PDR. Implementation entails the utilization of image preprocessing methods, including but not limited to RGB format conversion, 224×224 resizing, Gaussian blur filtration, and meticulous labeling. Cross-validation is performed by systematically dividing the dataset into ten folds.
- The proposed system achieved significant performance, reaching validation and training accuracy of 96.04% and 99.54%, respectively. Additional metrics such as recall, precision, and F1-score illustrate the model's efficacy in the domain of eye disease classification.

II. RELATED WORKS

The development of deep learning and machine learning techniques has sparked the interest of many researchers who aim to help medical professionals analyze fundus images. Numerous classification systems have been proposed over the years, and in the past few years, they have all improved dramatically. In [12], Logistic Regression (LR), Support Vector Machine (SVM), Decision Trees (DT), K-Nearest Neighbors (KNN), Random Forest (RF), and backpropagation were used for the early detection of eye diseases. This study also proposed a method based on Deep Convolutional Neural Networks (DCNN) to identify eye disorders. Image preprocessing methods, including grayscale, resizing, and power transformation, were applied to fundus images. For DR, the detection accuracy was 91%, for cataracts was 90%, and for glaucoma-affected images was 86%.

In [13], different CNN models were proposed to diagnose eye diseases using transfer learning from digitized retinal images. The DenseNet-201 model stood out with the best AUC-ROC (0.99), 100% specificity for AMD patients, 96.69% for GLC patients, 89.58% for healthy persons, and 89.52% for DR patients. In [14], VGG-16 was used for binary classification, increasing baseline accuracy from 89% to almost 91% and boosting the accuracy of glaucoma predictions from 54% to 91%, normal image predictions from 40% to 85.28%, and predictions of other diseases from 44% to 88%. In [15], 38,727 high-quality fundus images were used to train transfer learning models. The proposed method stood as an innovative deep transfer learning method, more suitable and more practically applicable to the public health systems of developing and growing nations. The proposed approach achieved classification accuracy of 87.4% for cataracts, 90.8% for DR, 87.5% for excavation, and 79.1% for blood vessels, all from low-quality images.

In [16], DL models were combined to classify fundus images into three categories: PDR, NPDR, and no DR. The model architectures used were Inception-ResNetV2 and DenseNet121. The MLP method was used to combine and categorize the features extracted from the two models. The proposed strategy outperformed a single model according to accuracy, average precision, recall (91%), and F1-score (90%). In [17], a method was proposed to learn unique characteristics from input images and then classify images into several disease categories using a modern DL model. The proposed system outperformed current methods in classifying eye diseases, achieving 97% accuracy with a modified EfficientNet-B3 model. In [18], a CNN model was used for eye disease classification, achieving an outstanding accuracy of 99.85%. This study showed that retinal fundus images can significantly improve the accuracy and effectiveness of treating eye problems. Table I provides a comparison between various studies for the detection of eye diseases using different techniques.

TABLE I. COMPARISON BETWEEN VARIOUS RELATED WORKS FOR EYE DETECTION USING DIFFERENT TECHNIQUES

	Methods & Models	**Diseases**	**Performance**	**Advantages**	**Research gaps and future work**
[4]	CNN	Various eye diseases	99.85% accuracy	Impressive accuracy rate	Exploration of model generalization, validation on diverse datasets
[12]	DCNN-based expert system	DR, Cataract, Glaucoma	91% (DR), 90% (Cataract), 86% (Glaucoma)	DCNN with one hidden layer	Used one simple model. Examine other neural networks and deep learning.
[13]	Transfer learning with CNN (DenseNet-201)	Healthy, DR, GLC, AMD	0.99 AUC. Specificity: 89.52%, 96.69%, 89.58%, 100%	DenseNet-201 outperformed other models	Areas for further exploration in transfer learning techniques, potential biases in the dataset
[14]	VGG-16, one versus rest strategy	Multiple (7 diseases + normal)	Increased from 89% to almost 91%, DR prediction increased from 54 to 91%	Significant improvement in prediction accuracy.	Further investigation on the impact of one versus rest strategy, exploration of additional diseases
[15]	Transfer learning with 38,727 high-quality images	Cataract, DR, Excavation, Blood Vessels	87.4%, 90.8%, 87.5%, 79.1%	Recognizing diseases in low-quality images	Investigation into ensemble learning optimization, exploration of other low-cost equipment
[16]	DenseNet121, Inception-ResNetV2, MLP	No DR, NPDR, PDR	91% accuracy and 90% F1-score	Improvement compared to a single model	Investigation into optimal fusion techniques for feature extraction
[17]	Modified EfficientNetB3	DR, Glaucoma, Cataract, Healthy	97% accuracy	Surpasses current approaches	Investigating the interpretability of the model, addressing potential biases

Despite significant advances of deep learning in diagnosing eye disorders using fundus images, several research gaps remain. Models that handle low-quality images and comprehensive detection of a broader range of eye conditions are needed. The integration of such models into practical, real-time diagnostic tools for public health systems is still limited. Furthermore, robust validation methods are necessary to ensure the generalizability of such models across diverse populations and imaging conditions. Addressing these gaps will enhance the efficacy and applicability of transfer learning in ophthalmology.

III. METHODOLOGY

This study used a DDR dataset, encompassing a collection of fundus images classified as normal, NPDR, and PDR. The preprocessing pipeline comprised several steps: converting images to RGB format, resizing them to 224×224 pixels, and filtering them using the Gaussian blur algorithm. For robust evaluation, the labeled dataset was subsequently divided by 10-fold cross-validation. A model was constructed by enhancing the EfficientNet-B5 architecture with further fully connected layers. The model was designed in the form of a sequential neural network, with the EfficientNetB5 base layer first, followed by flattening, dense, dropout, and finally, dense layers utilized for classification purposes. For training and evaluation, the following hyperparameters were established: a batch size of 32, 5 epochs, Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy as the loss function. This method seeks to utilize deep learning methods to accurately classify fundus images depicting eye diseases. Figure 1 depicts the method.

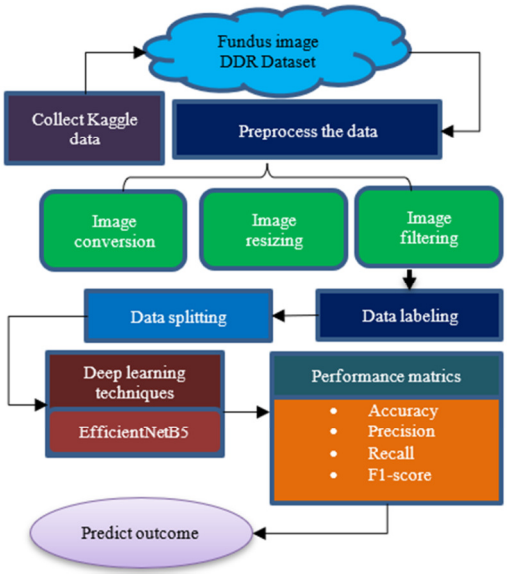

Fig. 1. Flow chart of the proposed method.

A. Data Collection and Preprocessing

This study used a DDR dataset from Kaggle [18, 19]. The DDR dataset is an essential collection of fundus images utilized in the study of ocular diseases. Preprocessing pipeline involved converting images to RGB format, resizing them to 224×224 pixels to standardize dimensions, and applying a Gaussian blur algorithm to filter the images. Moreover, detailed labeling techniques were used to organize images into three different classes. These preprocessing operations created a dataset that was meticulously organized to be used for training and assessment of DL models to classify specific diseased fundus images.

B. Data Splitting

A 10-fold cross-validation method was used. The dataset was segmented into ten subsets, in which the model was trained and verified step-by-step. In every iteration, one fold was used for validation and the other nine folds were used for training. This prevents the model from overfitting and helps to evaluate the model's performance in distinguishing diseases in retinal fundus images.

C. DL-Based Pre-Trained Model (EfficientNet-B5)

This study used the EfficientNet-B5 model as a basis for fundus image classification. Efficientnet-B5 uses the compound coefficients approach to enlarge the model, which is both easy and effective. EfficientNet encompasses several models for classifying images, one of which is Efficientnet-B5. Rather than random scaling network width, depth, and resolution, Efficientnet-B5 employs a fixed set of scaling coefficients to ensure consistent scaling. To provide an example, increasing network depth by α_N, breadth by β_N, and image size by γ_N may easily double the amount of computer resources required. The original tiny model was searched using a small grid to find the constant coefficients α, β, and γ. To evenly grow the network's width, depth, and resolution, Efficientnet-B5 employs a compound coefficient ϕ. The parameters used were 10 epochs, binary cross-entropy, 16 batch size, and Adam optimizer.

D. Model Training

The study used the EfficientNetB5 model as its basic framework, enhancing it with fully connected layers to produce a refined model specifically designed to classify diseases in fundus images. The model architecture is sequential, beginning with EfficientNet-B5 as a base and progressing through flattening layers, dense connections, dropout regularization, and a dense layer that performs classification into the three specified classes (normal, NPDR, and PDR). The selected hyperparameters for training were a batch size of 32, five epochs, the Adam optimizer, a learning rate of 0.0001, and categorical cross-entropy as a loss function. By striving for a harmonious equilibrium between model complexity and applicability, this configuration enhances learning efficiency and ensures precise classification of the test dataset.

Figures 2 and 3 illustrate the model architecture and summary. It is a sequential neural network composed of EfficientNet-B5 followed by layers that are densely connected to facilitate fine-tuning. With 28, 513, and 527 trainable parameters, the EfficientNetB5 base generates a tensor of the form None, 4, 4, and 2048. The resulting information is then compressed to 32,768 neurons, which are used as input for two dense layers with 512 neurons each, both fully connected. To avoid overfitting, dropout layers with zero dropout rates are

positioned after each dense layer. The output layer, comprising three neurons, is the last dense layer and is responsible for classifying fundus images into the specified categories, namely normal, NPDR, and PDR. In total, the model has 45,382,707 trainable parameters. The remaining 172,743 are non-trainable parameters derived from EfficientNet-B5. The primary objective is to efficiently extract features from fundus images to facilitate precise disease classification.

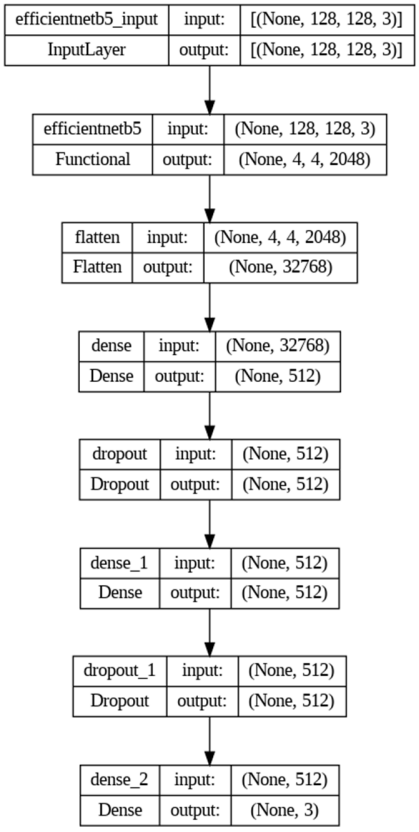

Fig. 2. Architecture of the proposed model.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb5 (Functional)  (None, 4, 4, 2048)       28513527

 flatten (Flatten)           (None, 32768)             0

 dense (Dense)               (None, 512)               16777728

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 512)               262656

 dropout_1 (Dropout)         (None, 512)               0

 dense_2 (Dense)             (None, 3)                 1539

=================================================================
Total params: 45,555,450
Trainable params: 45,382,707
Non-trainable params: 172,743
_________________________________________________________________
```

Fig. 3. Train summary of the proposed model.

E. Proposed Algorithm

Algorithm: **Proposed model based on EfficientNet-B5**
Input: Fundus image DDR dataset
Output: Eye disease classification
1: Start
2: Collect fundus image DDR dataset
3: Bring in certain Python modules, such as Matplotlib, OpenCV, TensorFlow, Keras, NumPy, Pandas, etc.
4: Perform data preprocessing on the dataset
  a) Convert into RGB format
  b) Resize into 224×224
  c) Image filtering using Gaussian blur
  d) Labeling and converting into three classes
5: Split dataset for 10-fold cross-validation
6: Apply EfficientNetB5 to train the model with
   hyperparameter settings:
  a) Epochs = 5
  b) Loss Function = categorical crossentropy
  c) Batch_Size = 32
  d) Optimizer = Adam()
7: Test the model
8: Calculate accuracy and loss

IV. RESULTS AND DISCUSSION

The proposed framework was executed on the Google Colab free cloud service using Python 3.7 and the widely used machine learning libraries Numpy, Pandas, TensorFlow, Keras, Sealborn, and Matprolib.

A. Dataset Visualization

This study used the DDR dataset [18, 19], which was made public in 2019. Several Chinese institutes contributed 13,673 fundus images covering 9,598 patients between 2016 and 2018. DDR fundus images were acquired using various camera models employing single-view capture. The data are classified into six classes: normal (6,266 records), mild NPDR (630 records), severe NPDR (236 records), PDR (913 records), moderate NPDR (4,477 records), and unclassified photos with poor quality (1151 records). Its extreme class imbalance should be taken into account. In [18], it was observed that small NPDR lesions on fundus images could be difficult to see and that certain severe NPDR classes might be easily confused for moderate ones. As a result, the dataset was resampled with only three categories to achieve balance: normal, NPDR (in which mild, moderate, and severe conditions were merged into a single category), and PDR. Subsequently, 913 data points were distributed across the classes, with the amount of the PDR class adjusted according to the distribution of training, validation, and test data. Figure 4 shows a list of images from the DDR dataset along with their respective numbers. On the healthy

retina, the absence of DR lesions is evident. In the presence of lesions, retinal manifestations of NPDR include exudates, MAs, and HAs. In the interim, the retina affected by PDR (advanced DR cases) develops new blood vessels. Figure 5 shows a count plot of all class labels that contain five classes, with the x-axis displaying labels and the y-axis showing the number of images. Figure 6 shows the multiclass data distribution labels for three classes: normal with 7266 images, NPDR with 5107 images, and PDR with 1149 images.

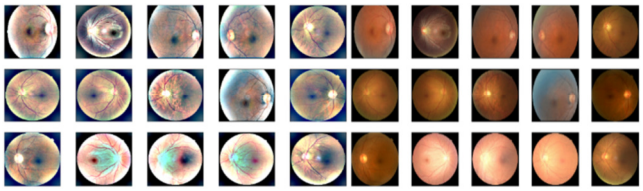

Fig. 4. Input images before and after preprocessing.

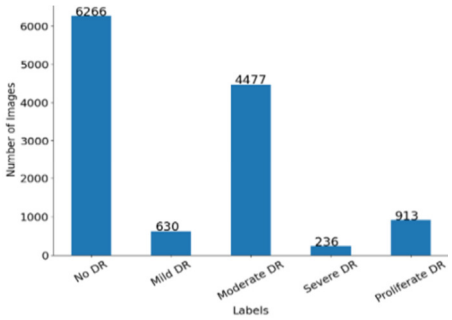

Fig. 5. Bar graph of count plot of all classes.

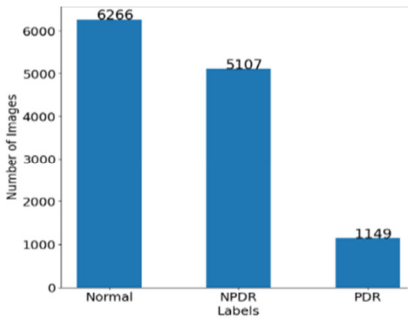

Fig. 6. Data distribution after resampling.

B. *Performance Evaluation Metrics*

Performance metrics were used to evaluate the proposed model. Equations (1)-(4) define accuracy, precision, recall, and F1 score, which are the most often used performance metrics in classification.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{N}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{F1} - \text{score} = \frac{2\times(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})} \quad (4)$$

These metrics are calculated using a confusion matrix, where TP, TN, FP, and FN represent different types of samples: true positives, true negatives, false positives, and false negatives, respectively. A 3×3 confusion matrix was used to evaluate classification. Figure 7 depicts the curves of the training and validation accuracy using the proposed model for 10 epochs. The training accuracy was 99.54% and the validation accuracy was 96.04%. After epoch 10, the training loss was approximately 0.0034% and the validation loss was 0.1983%. Further information about the testing performance of the model can be found in the confusion matrix.

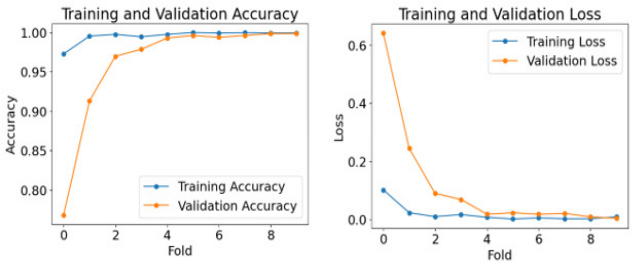

Fig. 7. Training and validation accuracy/loss of the proposed model for fundus image classification.

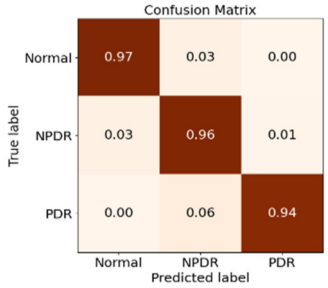

Fig. 8. Confusion matrix of the proposed model for fundus image classification.

Table II displays the performance of the proposed model. The model exhibited a remarkable training accuracy of 99.54%, which serves as an indication of its robust learning capacity throughout the training phase. The model showed high validation accuracy (99.04%), which reflects its ability to make predictions of new data based on information it had not encountered earlier. Furthermore, the effectiveness of the model in correctly identifying and classifying eye diseases from fundus images is evident through the high F1-score, recall, and precision values, which were 96.08%, 96.04%, and 96.02%, respectively. The evaluation results provide a complete picture of the impressive performance of the proposed model in the classification of fundus images.

TABLE II. MODEL'S PERFORMANCE

Parameters	Performance
Training accuracy	99.54
Validation accuracy	99.04
Precision	96.08
Recall	96.04
F1-score	96.02

Table III presents a comparative analysis of different models for fundus image classification. The proposed model outperformed other models, achieving higher accuracy, precision, recall, and F1 score. The DenseNet121 and InceptionResNetV2 models in [16] follow with an accuracy of 87%, matching their precision and recall at 87%, but having a slightly lower F1-score at 86.85%. The RF model in [20] shows moderate performance with an accuracy of 85.64%, precision and recall of 85.60%, and an F1-score of 85.50%. Lastly, the CNN model in [21] exhibits the lowest metrics, with an accuracy of 84%, precision of 85%, recall of 84.25%, and F1 score of 83.5%. This comparison highlights the superior performance of the proposed model, making it the most effective for fundus image classification among those evaluated.

TABLE III. COMPARISON BETWEEN MODELS FOR FUNDUS IMAGE CLASSIFICATION

Metrics	Proposed model	DenseNet121 & InceptionResNetV2 [16]	RF [20]	CNN [21]
Accuracy	99.04	87.00	85.64	84
Precision	96.08	87.00	85.60	85
Recall	96.04	87.00	85.60	84.25
F1-score	96.02	86.85	85.50	83.5

V. CONCLUSION AND FUTURE WORK

The eyes are the most important sensory organs in humans, accounting for up to 80% of all sensations. Eye-related disorders are a major concern. The possibility of early detection of DR is increasing due to advances in computing methods, such as AI and DL. This study examined and employed a deep transfer learning model for the identification of medical DR using a fundus image dataset that includes three categories: normal, NPDR, and PDR. The dataset images were enhanced using preprocessing, and the overfitting issue was addressed using cross-validation. EfficientNet-B5 was chosen as the base for the proposed model, which achieved 99.04% accuracy. This was supported by high precision (96.08%), recall (96.04%), and F1 score (96.02%). Furthermore, training time and computational complexity were reduced using a minimal number of layers in this model. Medical professionals could greatly benefit from this model, which could completely change the way eye diseases are diagnosed. Although the proposed model has the potential to be a valuable model, more research is needed to investigate further improvements.

REFERENCES

[1] P. Chakraborty and C. Tharini, "Pneumonia and Eye Disease Detection using Convolutional Neural Networks," *Engineering, Technology & Applied Science Research*, vol. 10, no. 3, pp. 5769–5774, Jun. 2020, https://doi.org/10.48084/etasr.3503.

[2] D. Helen and S. Gokila, "EYENET: An Eye Disease Detection System using Convolutional Neural Network," in *2023 2nd International Conference on Edge Computing and Applications (ICECAA)*, Namakkal, India, Jul. 2023, pp. 839–842, https://doi.org/10.1109/ICECAA58104.2023.10212139.

[3] S. Muchuchuti and S. Viriri, "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review," *Journal of Imaging*, vol. 9, no. 4, Apr. 2023, Art. no. 84, https://doi.org/10.3390/jimaging9040084.

[4] A. Saini, K. Guleria, and S. Sharma, "An Efficient Deep Learning Model for Eye Disease Classification," in *2023 International Research Conference on Smart Computing and Systems Engineering (SCSE)*, Kelaniya, Sri Lanka, Jun. 2023, vol. 6, pp. 1–6, https://doi.org/10.1109/SCSE59836.2023.10215000.

[5] Y. Zheng, M. He, and N. Congdon, "The worldwide epidemic of diabetic retinopathy," *Indian Journal of Ophthalmology*, vol. 60, no. 5, Oct. 2012, Art. no. 428, https://doi.org/10.4103/0301-4738.100542.

[6] R. Sarki, K. Ahmed, and Y. Zhang, "Early Detection of Diabetic Eye Disease through Deep Learning using Fundus Images," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 6, no. 22, May 2020, Art. no. 164588, https://doi.org/10.4108/eai.13-7-2018.164588.

[7] Z. S. Alzamil, "Advancing Eye Disease Assessment through Deep Learning: A Comparative Study with Pre-Trained Models," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14579–14587, Jun. 2024, https://doi.org/10.48084/etasr.7294.

[8] T. Pratap and P. Kokil, "Computer-aided diagnosis of cataract using deep transfer learning," *Biomedical Signal Processing and Control*, vol. 53, Aug. 2019, Art. no. 101533, https://doi.org/10.1016/j.bspc.2019.04.010.

[9] R. Asaoka *et al.*, "Using Deep Learning and Transfer Learning to Accurately Diagnose Early-Onset Glaucoma From Macular Optical Coherence Tomography Images," *American Journal of Ophthalmology*, vol. 198, pp. 136–145, Feb. 2019, https://doi.org/10.1016/j.ajo.2018.10.007.

[10] R. Sarki, K. Ahmed, H. Wang, Y. Zhang, J. Ma, and K. Wang, "Image Preprocessing in Classification and Identification of Diabetic Eye Diseases," *Data Science and Engineering*, vol. 6, no. 4, pp. 455–471, Dec. 2021, https://doi.org/10.1007/s41019-021-00167-z.

[11] T. Nazir, A. Irtaza, A. Javed, H. Malik, D. Hussain, and R. A. Naqvi, "Retinal Image Analysis for Diabetes-Based Eye Disease Detection Using Deep Learning," *Applied Sciences*, vol. 10, no. 18, Jan. 2020, Art. no. 6185, https://doi.org/10.3390/app10186185.

[12] D. Shamia, S. Prince, and D. Bini, "An Online Platform for Early Eye Disease Detection using Deep Convolutional Neural Networks," in *2022 6th International Conference on Devices, Circuits and Systems (ICDCS)*, Coimbatore, India, Apr. 2022, pp. 388–392, https://doi.org/10.1109/ICDCS54290.2022.9780765.

[13] K. Pin, J. H. Chang, and Y. Nam, "Comparative Study of Transfer Learning Models for Retinal Disease Diagnosis from Fundus Images," *Computers, Materials and Continua*, vol. 70, no. 3, pp. 5821–5834, Jan. 2022, https://doi.org/10.32604/cmc.2022.021943.

[14] A. Bali and V. Mansotra, "Transfer Learning-based One Versus Rest Classifier for Multiclass Multi-Label Ophthalmological Disease Prediction," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 12, 2021, https://doi.org/10.14569/IJACSA.2021.0121269.

[15] G. D. A. Aranha, R. A. S. Fernandes, and P. H. A. Morales, "Deep Transfer Learning Strategy to Diagnose Eye-Related Conditions and Diseases: An Approach Based on Low-Quality Fundus Images," *IEEE Access*, vol. 11, pp. 37403–37411, 2023, https://doi.org/10.1109/ACCESS.2023.3263493.

[16] R. H. Paradisa, A. Bustamam, W. Mangunwardoyo, A. A. Victor, A. R. Yudantha, and P. Anki, "Deep Feature Vectors Concatenation for Eye Disease Detection Using Fundus Image," *Electronics*, vol. 11, no. 1, Jan. 2022, Art. no. 23, https://doi.org/10.3390/electronics11010023.

[17] R. Sharma, J. Gangrade, S. Gangrade, A. Mishra, G. Kumar, and V. Kumar Gunjan, "Modified EfficientNetB3 Deep Learning Model to Classify Colour Fundus Images of Eye Diseases," in *2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA)*, Hamburg, Germany, Oct. 2023, pp. 632–638, https://doi.org/10.1109/ICCCMLA58983.2023.10346769.

[18] T. Li, Y. Gao, K. Wang, S. Guo, H. Liu, and H. Kang, "Diagnostic assessment of deep learning algorithms for diabetic retinopathy screening," *Information Sciences*, vol. 501, pp. 511–522, Oct. 2019, https://doi.org/10.1016/j.ins.2019.06.011.

[19] "DDR dataset." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/mariaherrerot/ddrdataset.

[20] M. M. Butt, D. N. F. A. Iskandar, S. E. Abdelhamid, G. Latif, and R. Alghazo, "Diabetic Retinopathy Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features," *Diagnostics*, vol. 12, no. 7, Jul. 2022, Art. no. 1607, https://doi.org/10.3390/diagnostics12071607.

[21] T. Babaqi, M. Jaradat, A. E. Yildirim, S. H. Al-Nimer, and D. Won, "Eye Disease Classification Using Deep Learning Techniques," in *Proceedings of the IISE Annual Conference & Expo 2023*, Jul. 2023.