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Identification of ocular disease from fundus images using CNN with transfer learning

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ABSTRACT

Eye diseases are one of the serious health problems affecting human life. Detecting and diagnosing them early is critical to prompt treatment and preventing vision loss. However, all studies in the field of eye disease classification using machine learning models are limited to the detection of single diseases, and the accuracy rate is still low in multi-class systems. In this study, we propose a multi-class classification model using four pre-trained CNNs (DenseNet121, ResNet50, EfficientNetB3 and VGG16). The model classified eye diseases into four categories: diabetic retinopathy, cataract, glaucoma, and normal. To improve the training process, another data augmentation technique is applied to increase the amount of data. The performance metrics of the system are calculated using the confusion matrix. DenseNet-121 shows excellent performance in retinal disease classification in 30 epochs of training, with training and test accuracy reaching 99.97% and 96.21% respectively. The implementation of this system should be considered as a very useful means to help ophthalmologists to rapid and precision detection of various eye diseases in the future.

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1. INTRODUCTION

According to the World Health Organization (WHO) [1], [2], it is estimated that approximately 2.2 billion people suffer from visual impairment. 1 billion of those cases could have been prevented or still have to be addressed. The leading causes of blindness or distance vision impairment among those mentioned 1 billion are cataracts (94 million) [3], refractive error (88.4 million), age-related macular degeneration (8 million), glaucoma (7.7 million) [4] and diabetic retinopathy (3.9 million) [5]. Early detection of eye diseases is crucial in the treatment especially that they are the main cause of blindness around the world and some of them have irreversible effects. Common eye diseases are:

Cataract: cataracts are the transparency loss of crystalline lens area as shown in Figure 1, which occurs when the protein inside the lens clumps together [6] it causing the eyes to be cloudy, vision to be frosty or fogged-up and the person suffering from it to face difficulties reading, driving, and even recognizing another person's face.

Glaucoma: The second leading cause of blindness in the world, 50% of people with glaucoma don't know they have it as there are usually no early symptoms [7] as shown in Figure 2 caused by fluid building up in the front part of the eyes that increases the pressure inside the eye causing the optic nerve that connects the eye to the brain to be damaged [8].

Diabetic Retinopathy: DR is a complication of diabetes that causes the blood vessels of the retina to swell and to leak fluids and blood as shown in Figure 3. DR can lead to a loss of vision if it is in an advanced stage. Worldwide, DR causes 2.6% of blindness [9], [10]. The possibility of DR presence increases for diabetes patients who suffer from the disease for a long period [11].

Figure 1. Fundus of the eye with Cataract

Figure 2. Fundus of the eye with Glaucoma

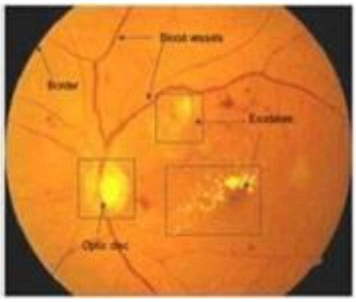


Figure 3. Retinal fundus images of Diabetic retinopathy

Early detection of eye diseases plays a crucial role in alleviating the majority of cases of visual impairment to minimize the risk of blindness in affected individuals. Manual lesion detection is time-consuming and may lack the desired accuracy. Many automated systems have been developed recently to help ophthalmologists in their work, Deep learning (DL) methods have gained popularity for detecting various human diseases due to their high performance and superior accuracy [12].

Several research studies have shown that DL models provide superior accuracy in the field of visual impairment detection. For instance, in [13] research was conducted to detect eye disease in fundus images using convolutional neural network (CNN) using MobileNetV2 architecture with a dataset of fundus images consisting of 601 images divided into 2 normal and abnormal classes (cataract, glaucoma, and retinal disease) get an accuracy value of 72%, precision of 72%, recall of 72%, and F1-Score of 72%. A model proposed in [14] presented a neural network-based framework to analyze early eye sicknesses of the patients. They used multi-facet feedforward networks with a solitary secret layer. The Backpropagation calculation is utilized for preparing the organizations in an administered mode and achieved 87% accuracy.

The main objective of the work in [15] was to create an automatic image-level diabetic retinopathy detection using three DL models which were Inception V3, ResNet151, and Inception-ResNet-V2. They individually performed with an accuracy of 87.91%, 87.20% and 86.18% respectively. The idea of [16] was to examined the performance of four pretrained CNN models, including DenseNet121, InceptionV3, Xception, and InceptionResNetV2, to diagnose cataracts from retinal images. Moreover, the authors discovered that InceptionResNetV2 outperforms all other models, with a two-class classification with accuracy of 98.17%.

A study [17] suggests a method using the CNN method for the detection of retinal eye disease. They used multiple classes of diabetic eye disease, and the model was tested on various retinal fundus images collected from a public dataset and described by an ophthalmologist. Overall, 81.33% ACC, 100% sensitivity, and 100% specificity were achieved for multiclass classification. For a multiclass classification system using DL approach to detection of Cataract, Diabetic Retinopathy and Glaucoma Eye Diseases has been suggested in this research [18] The data set used for disease detection includes a total of 2748 Retinal Fundus images taken from 1374 normal individuals and 1374 different disease groups. the results obtained with the EfficientNet architecture were measured as 94.88% for Accuracy.

The authors of this paper [19] classified eye disease conditions into three classes, namely normal, cataract, and glaucoma using a CNN with EfficientNet architecture the dataset in this paper is obtained from Kaggle totaling 300 images which resulted in the highest accuracy with 79.22% accuracy, 80.3% precision value, 79.22% recall value, 78.87% F1-Score. In [20] the authors present a classification system of fundus images, including images of healthy patients as well as those with diabetic retinopathy, cataracts, and glaucoma, using CNN and several pretrained models. the better results obtained are for GoogleNet, ResNet 18, VGG 19, and AlexNet with the SGDM optimiser (92.7%, 92.1%, 87.9%, and 88.9%, respectively), and 88.3%, 87.1% for ResNet 18 and VGG19, respectively, with the Adam optimizer.

2. METHOD

This research paper presents a model of eye diseases using retinal fundus images. Figure 4 represent the proposed system for retinal disease classification. The proposed architecture includes different steps: data acquisition, the preprocessing phase, the partitioning phase and training of different models of CNN finally the performance of this approach is assessed using accuracy metrics and compared with previous research.

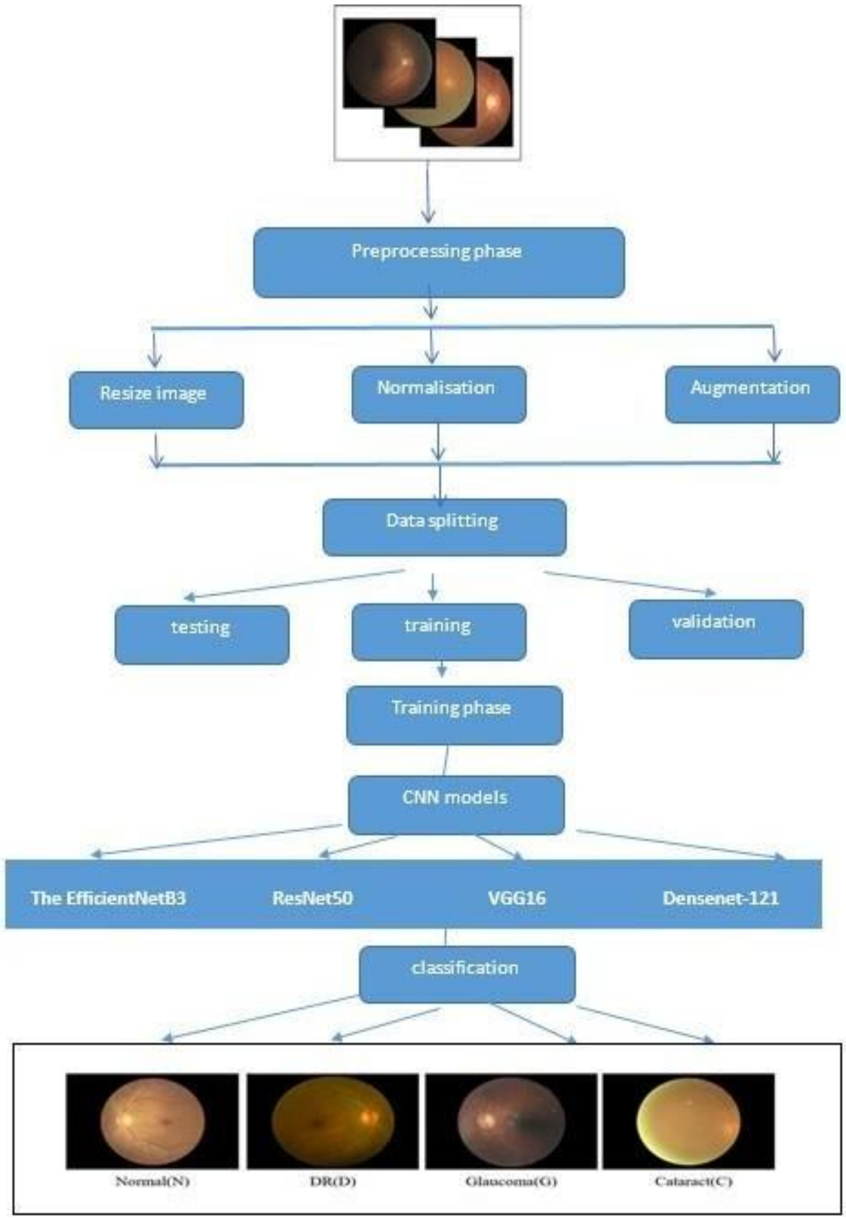
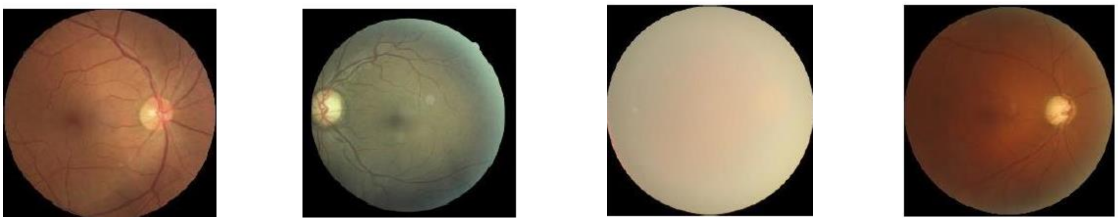


Figure 4. Architecture of the proposed retinal disease classification system

2.1. Dataset

The eye diseases dataset has been obtained from publicly available source Kaggle (https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification), this dataset is one of the most comprehensive resources available to the public on Kaggle for detecting eye diseases. This dataset comprises a diverse collection of retinal images categorized into four distinct disease types: Normal, Diabetic Retinopathy, Cataract, and Glaucoma. There is total 4,217 images can be observed in Figure 5. Figure 5(a) presents normal retina fundus, Figure 5(b) displays retinal of diabetic retinopathy, Figure 5(c) shows retinal with cataract, and Figure 5(d) presents retinal signs of glaucoma while Table 1 gives the details and statistics about the dataset.



(a) (b) (c) (d)

Figure 5. Retina fundus of (a) normal, (b) diabetic retinopathy, (c) cataracts, and (d) glaucoma

Table 1. Distribution of images in the dataset

No. of classes	Diseases	Total image
1	Diabetic Retinopathy	1098
2	Cataract	1038
3	Glaucoma	1007
4	Normal	1074

The dataset needs to be split into three different sets: Training, Validation, and Test. allocating 70% of the data for the training set, 15% for the validation set, and the remaining 15% for the testing set. The training set is the set of data used to train the model. It comprises a large portion of the available data and is the basis for model parameter estimation, the validation set was employed to assess and validate the trained models while the test set is the set of data used to evaluate the final performance of a trained model.

2.2. Preprocessing

Image pre-processing is the preliminary stage in algorithm model building, it has been performed on fundus images of dataset to make dataset suitable for training process and to initialize it for the extract the feature. It consists of 3 steps: Resize images is a process of changing the large size of several images to become the same size to facilitate the image classification detection process, the image size used was 224*224. Additionally, normalization is a process of changing the scale of image pixel values to have the same range of values. Pixel value is a numerical value that has a level of brightness or brightness of a pixel and the Data Augmentation this step is used in the pre-processing stage to increase the proposed system's efficiency for precise evaluation. It increases the dataset by supplying more images to be used in the training and testing stages. Moreover, it will tackle the problem of overfitting. These techniques are: Horizontal Flip, Zoom Range, Rotation Range and Fill Mode.

2.3. Deep learning

DL is one of the Machine Learning fields based on artificial neural networks. In DL there are many hidden layers that are modeled in such a way as to provide accurate output. The performance of DL teaches computers to process data like the human brain. it makes it possible to recognize and classify text, images, moving images, and audio [21].

2.4. Convolutional neural networks

CNN is a class of DL neural it is a special neural network type that has good performance in image classification it can recognize various objects after training on a large dataset. It can detect diseases within seconds that are difficult to recognize manually. The CNN takes images as input for encoding characteristics into architecture making forward function implementation efficient and reduction of network parameters, neurons in CNN layers are arranged in three dimensions. CNN is comprised of a minimum of 5 layers. Input 3D data is transformed into 3D output using a differentiable function. There are three components in CNN. The convolutional layer is the first one that is used for identifying patterns in the entire image. Secondly, the max-pooling layer is used for performing down sampling and thirdly the fully connected dense layer is used to output results [22].

2.5. Transfer learning

TL is the technique of transferring information from one domain to another [23]. Alternative for feature extraction and categorization TL stands for carried out with the use of a deep CNN model that has been in terms of DL, it had already been trained on a large dataset. Because fine-tuning a CNN model that has already been trained is usually faster, and considerably less time-consuming than training a CNN model with random data. TL has recently been updated to include weights that have been initialized from the start [24].

2.5.1. Visual geometry group Visual geometry group (VGG16)

The VGG-16 architecture is a CNN designed for image classification tasks. It was introduced by the Visual Geometry Group at the University of Oxford [25]. VGG-16 is characterized by its simplicity and uniform architecture, making it easy to understand and implement. This model employs 16 layers are organized into blocks, with each block containing multiple convolutional layers followed by a max-pooling layer for downsampling [26].

2.5.2. Residual networks residual network (ResNet50)

ResNet50 is a 50-layer CNN. ResNet50 is a 48-layer residual network with one max pool layer and one average pool layer. that excels at image classification. It's like a highly trained image analyst who can dissect a picture, identify objects and scenes within it, and categorize them accordingly [27], [28].

2.5.3. The EfficientNetB3

The EfficientNetB3 is the third model in the EfficientNet family it is an image classification models which achieve state-of-the-art ACC while being an order of magnitude smaller and faster than other models. The EfficientNetB3 can capture more fine-grained details in the input images due to having more filters per layer and a higher spatial resolution, it is a cost-efficient, robust model [29].

2.5.4. DenseNet 121

DenseNet is a network architecture where each layer is directly connected to every other layer in a feed- forward fashion [30]. For each layer, the feature maps of all preceding layers are treated as separate inputs whereas its own feature maps are passed on as inputs to all subsequent layers. DenseNets have several compelling advantages: they alleviate the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters [31].

2.6. Training

Convolutional Neural Network, which is one of the most popular algorithms for DL, different transfer learning architectures are implemented in the detection of diabetic retinopathy, cataract, glaucoma [32]. In this work CNN was used to train the model using four different classes: cataract, diabetic retinopathy, glaucoma and normal in order to classify retinal images. For feature extraction, the researcher used different pre-trained models such as DesnseNet121, EfficientNetB, ResNet50, and VGG16 were used with adding Global Average Pooling layer, dropout layer and Dense layer at the beneath of base model. The image size used was 224*224. Training and Validation of each model is trained and tested with augmentation images with different learning rates, the initial learning rate was set to 0.001, which was subsequently reduced to 0.0001, 30 epochs which is further divided into 10 steps with a batch size of 40 images which had a notable impact on the classification performance of the model
the desired classification into four classes.

2.7. Evaluating performance using performance matrix

The confusion matrix is a diagram that describes in detail the model's performance. In the confusion matrix, there are four categories:
True Positive (TP), which denotes a true positive prediction.
True Negative (TN), which denotes a true negative prediction.
False Positive (FP), which denotes a false positive prediction.
False Negative (FN), which denotes a false negative prediction.

The results of the confusion matrix are used to determine the accuracy, precision, recall, and F1 score to make performance comparisons of the models. The formulas used as measurement metrics in the literature [33] are given.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{F1 score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{4}$$

Accuracy is one of the evaluation criteria used to determine the feasibility of the system in data classification. Recall is a parameter used to determine the quantity and Precision is a parameter used to determine quality finally The F1 score is a method for determining the recall and accuracy of a model.

3. RESULTS AND DISCUSSION

In this work, this model is implemented using Keras with TensorFlow on GoogleColab with GPU. Different pre-trained models such as DenseNet121, EfficientNetB, ResNet50, and VGG16 were used, this study used a dataset consisting of retinal fundus images, encompassing various conditions such as cataract, diabetic retinopathy, glaucoma and normal case. It was observed that using a larger batch size resulted in worse validation loss, several optimizers have been tested as Adam, SGD, RMSprop, Adamax, but Adamax optimizer works better than others it is the most popular optimizer these days. Adam generally requires a lower learning rate. The different Transfer Learning model used in this work were tested on the same database and we calculated evaluating performance using the confusion Matrix the results of this are used to determine the accuracy, precision, recall, and F1 score to make performance comparisons of the models.

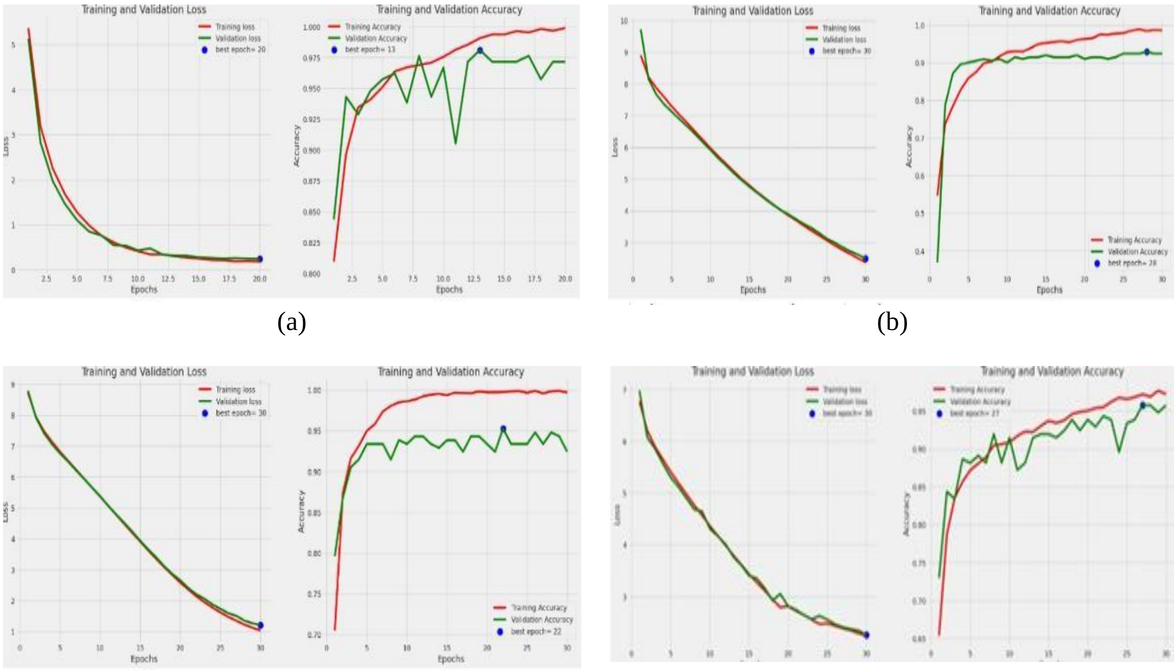
Table 2 shows the accuracy, precision, recall, and f1-score results obtained using the four models to classified the same categories (cataract, diabetic retinopathy, glaucoma, and normal). In this study that the DenseNet 121 model, which used the pre-trained model, achieved higher accuracy of 96.20 % compared to the EfficientNetB3 model, VGG16 model and ResNet50 Model which achieved a classification accuracy of 92.41%, 93.36% and 93.84% respectively. It can also be seen that the F1-score of Diabetic retinopathy is 100 %, the results of the other classes (Normal, Cataract, and Glaucoma) are better for the DenseNet121 in all evaluation metrics in Table 2.

Table 2. Evaluation metrics for the different model of classification

Model	Class	Precision	Recall	f1-score	Accuracy
DenseNet 121	cataract	**0.98**	0.96	0.97	
	diabetic_retinopathy	**1.00**	1.00	1.00	**96.20%**
	glaucoma	**0.98**	0.90	0.94	
	Normal	**0.90**	0.98	0.94	
The EfficientNetB3	cataract	0.91	0.94	0.93	
	diabetic_retinopathy	1.00	1.00	1.00	92.41%
	glaucoma	0.92	0.82	0.87	
	Normal	0.87	0.94	0.90	
VGG16	cataract	0.92	1.00	0.96	
	diabetic_retinopathy	1.00	1.00	1.00	93.36%
	glaucoma	0.87	0.87	0.87	
	Normal	0.95	0.88	0.91	
ResNet50	cataract	0.98	1.00	0.99	
	diabetic_retinopathy	1.00	1.00	1.00	93.84%
	glaucoma	0.96	0.81	0.88	
	Normal	0.84	0.96	0.90	

An accuracy comparison of the four training and testing processes are in Figure 6. The maximal training and validation accuracy of the DenseNet 121 is shown in Figure 6(a) during the training and validation periods. At epoch 20, DenseNet 121 architecture the achieved results demonstrated remarkable accuracy, with a 96.20% and the precision was 98%. The accuracy and loss for EfficientNetB3, ResNet50 and VGG16, model is shown in Figures 6(b)-(d), respectively.

The results show that the proposed method is feasible and effective in classifying and detecting eye diseases. In terms of methodology, a notable distinction can be made between this study and previous research efforts. For example, in [34] the authors introduced DL architecture for detection of ocular disease achieved 95.17%. Furthermore, explored visual impairments utilizing ResNet-50+ Fine-tuning achieving an accuracy of 92% [35], on the other had in [36] the efficientNet B0 and MobileNetV3 models are used this study attained an accuracy of 94% and 73% respectively. Similarly, in [37] presented a study on visual impairments using the CNN model achieving an accuracy of 94%. In comparison, this study achieved a high accuracy rate an accuracy of 96.2% using the DenseNet121 model. The proposed model was presented and its effectiveness in classifying eye diseases was compared with previous studies that use the same categories (cataract, diabetic retinopathy, glaucoma, and normal retinal images) and the same dataset used in our research. Table 3 shows a comparison between the current studies and our research Based on Table 3, it can be noted that this research demonstrates better accuracy compared to previous studies used as references.



(a) (b)

(c) (d)

Figure 6. Training accuracy and lossL: (a) for DenseNet121 model, (b) EfficientNetB3 model, (c) for ResNet50 model, and (d) VGG16 model

Table 3. Comparison of our work with very recent work

Study	Year	dataset	Model	Test accuracy
Proposed model	2024	Kaggel	DenseNet121	96.20%
[34]	2023	Kaggel	Deep learning	95.17%
		(4217 images)		
[35]	2023	IDRiD	ResNet-50 &	92%
		4217	Fine-tuning	
[36]	2023	Kaggel	The EfficientNet-B0	94%
		(4217 images)	MobileNetV3	73%
[37]		Kaggel		
	2023	(4217 images)	CNN	94%

4. CONCLUSION

Eye diseases such as cataracts, glaucoma and diabetic retinopathy are well-known forms of visual impairment that affect a significant number of people worldwide. Creating a highly effective automated diagnostic system for eye diseases represents a substantial step forward in addressing global health challenges, as early detection of these diseases is crucial to avoiding blindness. The model proposed in this study is trained using four pre-trained CNNs (DenseNet121, ResNet50, EfficientNet-b3, VGG16), these were applied to the same dataset. The model classified the retinal image into four categories: diabetic retinopathy, cataract, glaucoma, and normal, this study improved on previous research classifying eye diseases using the DenseNet 121 model. The system was able to detect better than all other models used and produced results with a performance accuracy value of 96.20%. Future work will focus on adding new diseases to the model. We will also attempt to classify in depth the stage of each types of visual impairments. Additionally, creating a web or mobile application to early disease detection, these disorders can be detected and diagnosed early enough to not only cure but also avoid permanent blindness.

REFERENCES

[1] T. R. Fricke *et al.*, "Global prevalence of presbyopia and vision impairment from uncorrected presbyopia: systematic review, meta-analysis, and modelling," *Ophthalmology*, vol. 125, no. 10, pp. 1492–1499, Oct. 2018, doi: 10.1016/j.ophtha.2018.04.013.

[2] X. Q. Zhang, Y. Hu, Z. J. Xiao, J. S. Fang, R. Higashita, and J. Liu, "Machine learning for cataract classification/grading on ophthalmic imaging modalities: a survey," *Machine Intelligence Research*, vol. 19, no. 3, pp. 184–208, May 2022, doi: 10.1007/s11633-022-1329-0.

[3] I. Weni, P. E. P. Utomo, B. F. Hutabarat, and M. Alfalah, "Detection of cataract based on image features using convolutional neural networks," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 15, no. 1, p. 75, Jan. 2021, doi: 10.22146/ijccs.61882.
[4] S. Muchuchuti and S. Viriri, "Retinal disease detection using deep learning techniques: a comprehensive review," *Journal of Imaging*, vol. 9, no. 4, p. 84, Apr. 2023, doi: 10.3390/jimaging9040084.
[5] M. Z. Atwany, A. H. Sahyoun, and M. Yaqub, "Deep learning techniques for diabetic retinopathy classification: a survey," *IEEE Access*, vol. 10, pp. 28642–28655, 2022, doi: 10.1109/ACCESS.2022.3157632.
[6] P. A. Asbell, I. Dualan, J. Mindel, D. Brocks, M. Ahmad, and S. Epstein, "Age-related cataract," *Lancet*, vol. 365, no. 9459, pp. 599–609, Feb. 2005, doi: 10.1016/S0140-6736(05)70803-5.
[7] S. Maheshwari, R. B. Pachori, and U. R. Acharya, "Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 3, pp. 803–813, May 2017, doi: 10.1109/JBHI.2016.2544961.
[8] T. J. Jun *et al.*, "TRk-CNN: transferable ranking-CNN for image classification of glaucoma, glaucoma suspect, and normal eyes," *Expert Systems with Applications*, vol. 182, p. 115211, Nov. 2021, doi: 10.1016/j.eswa.2021.115211.
[9] W. L. Alyoubi, W. M. Shalash, and M. F. Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review," *Informatics in Medicine Unlocked*, vol. 20, p. 100377, 2020, doi: 10.1016/j.imu.2020.100377.
[10] L. Akshita, H. Singhal, I. Dwivedi, and P. Ghuli, "Diabetic retinopathy classification using deep convolutional neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 24, no. 1, pp. 208–216, Oct. 2021, doi: 10.11591/ijeecs.v24.i1.pp208-216.
[11] A. A. Abdullah, A. Aldhahab, and H. M. Al Abboodi, "Review of eye diseases detection and classification using deep learning techniques," *BIO Web of Conferences*, vol. 97, p. 12, 2024, doi: 10.1051/bioconf/20249700012.
[12] Rajatha and A. D. Virupakshappa, "Unveiling visionary frontiers: a survey of cutting-edge techniques in deep learning for retinal disease diagnosis," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 2, pp. 1261–1272, Feb. 2024, doi: 10.11591/ijeecs.v33.i2.pp1261-1272.
[13] R. Indraswari, W. Herulambang, and R. Rokhana, "Ocular Disease Detection on Fundus Images Using Convolutional Neural Network (CNN)," *Techno.Com*, vol. 21, no. 2, pp. 378–389, May 2022, doi: 10.33633/tc.v21i2.6162.
[14] R. Sarki, K. Ahmed, H. Wang, and Y. Zhang, "Automated detection of mild and multi-class diabetic eye diseases using deep learning," *Health Information Science and Systems*, vol. 8, no. 1, Oct. 2020, doi: 10.1007/s13755-020-00125-5.
[15] H. Jiang, K. Yang, M. Gao, D. Zhang, H. Ma, and W. Qian, "An interpretable ensemble deep learning model for diabetic retinopathy disease classification," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, Jul. 2019, pp. 2045–2048, doi: 10.1109/EMBC.2019.8857160.
[16] M. K. Hasan *et al.*, "Cataract disease detection by using transfer learning-based intelligent methods," *Computational and Mathematical Methods in Medicine*, vol. 2021, pp. 1–11, Dec. 2021, doi: 10.1155/2021/7666365.
[17] R. Sarki, K. Ahmed, H. Wang, Y. Zhang, and K. Wang, "Convolutional neural network for multi-class classification of diabetic eye disease," *EAI Endorsed Transactions on Scalable Information Systems*, vol. 9, no. 4, p. 172436, Jul. 2022, doi: 10.4108/eai.16-12-2021.172436.
[18] G. Arslan and Ç. B. Erdaş, "Detection of cataract, diabetic retinopathy and glaucoma eye diseases with deep learning approach," *Intelligent Methods In Engineering Sciences*, Jun. 2023, doi: 10.58190/imiens.2023.11.
[19] Z. Arif, R. Y. Nur Fu'adah, S. Rizal, and D. Ilhamdi, "Classification of eye diseases in fundus images using Convolutional Neural Network (CNN) method with EfficientNet architecture," *JRTI (Jurnal Riset Tindakan Indonesia)*, vol. 8, no. 1, p. 125, Jul. 2023, doi: 10.29210/30032835000.
[20] S. Benbakreti, S. Benbakreti, and U. Ozkaya, "The classification of eye diseases from fundus images based on CNN and pretrained models," *Acta Polytechnica*, vol. 64, no. 1, pp. 1–11, Mar. 2024, doi: 10.14311/ap.2024.64.0001.
[21] M. S. Khan *et al.*, "Deep learning for ocular disease recognition: an inner-class balance," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–12, Apr. 2022, doi: 10.1155/2022/5007111.
[22] N. Abou Baker, N. Zengeler, and U. Handmann, "A transfer learning evaluation of deep neural networks for image classification," *Machine Learning and Knowledge Extraction*, vol. 4, no. 1, pp. 22–41, Jan. 2022, doi: 10.3390/make4010002.
[23] M. K. Jabbar, J. Yan, H. Xu, Z. U. Rehman, and A. Jabbar, "Transfer learning-based model for diabetic retinopathy diagnosis using retinal images," *Brain Sciences*, vol. 12, no. 5, p. 535, Apr. 2022, doi: 10.3390/brainsci12050535.
[24] R. Amin, A. Ahmed, S. Shabih Ul Hasan, and H. Akbar, "Multiple eye disease detection using deep learning," *Foundation University Journal of Engineering and Applied Sciences (HEC Recognized Y Category , ISSN 2706-7351)*, vol. 3, no. 2, pp. 14–26, Jan. 2023, doi: 10.33897/fujeas.v3i2.689.
[25] M. Erdin and P. L. Patel, "Early detection of eye disease using CNN," *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 4, pp. 2683–2690, Apr. 2023, doi: 10.22214/ijraset.2023.50737.
[26] S. Adebayo, H. O. Aworinde, A. O. Akinwunmi, A. Ayandiji, and A. O. Monsir, "Convolutional neural network-based crop disease detection model using transfer learning approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 1, pp. 365–374, Jan. 2023, doi: 10.11591/ijeecs.v29.i1.pp365-374.
[27] A. K. Bitto and I. Mahmud, "Multi categorical of common eye disease detect using convolutional neural network: a transfer learning approach," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 4, pp. 2378–2387, Aug. 2022, doi: 10.11591/eei.v11i4.3834.
[28] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2016, vol. 2016-Decem, pp. 770–778, doi: 10.1109/CVPR.2016.90.
[29] W. Nuipian, P. Meesad, and S. Kanjanawattana, "A comparative ResNet-50, inceptionV3 and efficientNetB3 with retinal disease," in *ACM International Conference Proceeding Series*, Dec. 2023, pp. 283–287, doi: 10.1145/3639233.3639337.
[30] G. Huang, Z. Liu, G. Pleiss, L. van der Maaten, and K. Q. Weinberger, "Convolutional vetworks with dense connectivity," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 12, pp. 8704–8716, Dec. 2022, doi: 10.1109/TPAMI.2019.2918284.
[31] G. H. Vardhan, M. V. S. Jyoshna, and P. K. Viswanath "Diabetic Retinopathy Detection Using InceptionResnet-V2 and Densenet121"Journal of Image Processing and Intelligent Remote Sensing Vol: 04, No.02, Feb-Mar 2024.doi: 10.55529/jipirs.42.30.40.
[32] T. Afroze, S. Akther, M. A. Chowdhury, E. Hossain, M. S. Hossain, and K. Andersson, "Glaucoma detection using inception convolutional neural network V3," in *Communications in Computer and Information Science*, vol. 1435, Springer International Publishing, 2021, pp. 17–28.

[33] H. Çetiner and İ. Çetiner, "Classification of Cataract Disease with a DenseNet201 Based Deep Learning Model "Journal of the Institute of Science and Technology, vol 12(3): pp 1264 - 1276, September 2022 DOI: 10.21597/jist.1098718.
[34] P. Kumar, S. Bhandari, and V. Dutt, "Pre-trained deep learning-based approaches for eye disease detection," in *Proceedings of the International Conference on Circuit Power and Computing Technologies, ICCPCT 2023*, Aug. 2023, pp. 1286–1290, doi: 10.1109/ICCPCT58313.2023.10245175.
[35] H. Imaduddin, I. C. Utomo, and D. A. Anggoro, "Fine-tuning ResNet-50 for the classification of visual impairments from retinal fundus images," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 4, pp. 4175–4182, Aug. 2024, doi: 10.11591/ijece.v14i4.pp4175-4182.
[36] S. Prasher, L. Nelson, and S. Gomathi, "Automated eye disease classification using MobileNetV3 and EfficientNetB0 models using transfer learning," in *2023 World Conference on Communication and Computing, WCONF 2023*, Jul. 2023, pp. 1–5, doi: 10.1109/WCONF58270.2023.10235193.
[37] T. Babaqi, M. Jaradat, A. E. Yildirim, S. H. Al-Nimer, and D. Won, "Eye disease classification using deep learning techniques," *Proceedings of the IISE Annual Conference and Expo*, 2023.

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