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Fine-tuning ResNet-50 for the classification of visual impairments from retinal fundus images

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ABSTRACT

The sense of sight plays a crucial role in human perception, as it serves as our primary sensory organ for perceiving light. However, a considerable number of individuals experience a wide range of vision impairments. These impairments encompass diverse conditions such as diabetic retinopathy, glaucoma, and cataracts. Each visual impairment exhibits unique characteristics and symptoms, highlighting the need for timely and accurate detection to facilitate appropriate treatment and prevent vision loss. This research aims to develop a deep learning-based system specifically designed to detect visual impairments. The proposed solution involves creating a model using the ResNet-50 algorithm as the foundational methodology, and fine-tuning multiple parameters to enhance the model's performance. The research utilizes a dataset consisting of retinal fundus images, which are categorized into four distinct classes: diabetic retinopathy, glaucoma, cataracts, and normal. The findings demonstrate the effectiveness of the model, achieving an impressive accuracy score of 92%. This signifies a significant improvement of 6% over the accuracy achieved in the previous study, which stood at 86%. The implementation of this system is expected to make a significant contribution to the rapid and accurate detection of various eye disorders in the future, enabling timely intervention and prevention of visual impairment.

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1. INTRODUCTION

Visual impairment is a prevalent global condition that continues to increase in incidence. Cataracts, glaucoma, and diabetic retinopathy are among the recognized forms of visual impairments. According to the World Health Organization (WHO), there are at least 2.2 billion individuals worldwide affected by visual impairments [1]. Cataracts account for the highest number of cases, with approximately 65.2 million affected individuals, making them the leading cause of blindness compared to other ocular disorders [2]. ataracts occur due to the aggregation of proteins, resulting in the loss of lens transparency. Multiple factors contribute to the development of cataracts, including developmental abnormalities, trauma, metabolic disorders, genetics, drug-induced changes, and aging [3]. Genetics and aging are the two most common causes of cataracts. Glaucoma, the second most common visual disorder, is characterized by progressive degeneration of the optic nerve, loss of retinal ganglion cells, thinning of the retinal nerve fiber layer, and increased excavation of the optic disc [4]. Glaucoma, the second most common visual disorder, is characterized by progressive degeneration of the optic nerve, loss of retinal ganglion cells, thinning of the retinal nerve fiber layer, and increased excavation of the optic disc [5]. Glaucoma, along with cataracts and diabetic retinopathy, is a leading cause of blindness. It can be described as optic neuropathy, primarily caused by increased pressure on the eye, resulting in damage to the optic nerve, which serves as a vital connection between the brain and the eye. Although glaucoma can occur at any age, it predominantly affects individuals over the age of 60. Lastly, diabetic retinopathy is an eye disease that frequently affects individuals with diabetes and, if left untreated, can lead to complete blindness. The retina, a light-sensitive membrane at the back of the eye, plays a crucial role in converting light into electrical signals, which are then transmitted to the brain through the nervous system. Diabetic retinopathy occurs due to damage, fluid leakage from impaired blood vessels within the retinal tissue, or blockage of retinal blood vessels caused by high blood sugar levels. These conditions can result in vision distortion [6].

The timely detection, careful monitoring, and prompt intervention play a crucial role in mitigating the majority of visual impairment cases. A notable example is the importance of early detection and treatment of diabetic retinopathy due to its progressive nature and the impact of lesion quantity and type on disease severity, as observed in fundus images [7]. Swiftly addressing visual impairments is crucial to minimize the risk of blindness among affected individuals. Detection models are needed to recognize various symptoms of visual impairment to make an accurate diagnosis. Deep learning methods have gained popularity in the detection of various diseases in humans due to their high performance and superior accuracy. These techniques have made significant contributions to the detection of ocular diseases through image processing [8].

Previous research studies have shown that deep learning models provide superior accuracy when used to detect visual impairment. For instance, Bulut *et al.* [9] conducted a study focusing on the classification of retinal diseases using the EfficientNet model. The study achieved noteworthy results, with a sensitivity of 0.9439, a specificity of 0.8604, and an overall accuracy (ACC) of 0.86 [9]. In a similar vein, Ahmed and Hameed [10] employed the backpropagation artificial neural network (BPANN) to classify ocular diseases, resulting in an accuracy of 85.26315%. On other research Ahmed and Hameed [11] conducted research to classify eye diseases using the color histogram feature and hierarchal multi-label classification (HMC). The dataset used comes from a digital camera to classify external eye disease. The result of this research is an accuracy of 75.7% [11]. Ramanathan *et al.* [12] proposed an effective method to classify diabetic retinopathy from retinal images. At first the wiener filter was used for preprocessing, then the preprocessed images were segmented using the c-mean fuzzy technique. Then from the segmented image, the features are extracted using a gray level co-occurrence matrix (GLCM). Inception V3 model is used in the classification process to classify the image. The results of this study obtained an accuracy of 95% [12]. Devi and Kumar [13] conducted research to identify diabetic retinopathy. The dataset used comes from the Kaggle Asia pacific tele-ophthalmology society blindness. The method used is gaussian blur for data augmentation and ResNet-50 without fine tuning. the study obtained an accuracy of 91% using synthetic data and 86% on non-synthetic data [13]. Similarly, Verma *et al.* [14] focused on glaucoma detection using the support vector machine (SVM) method, with K-means employed as a comparative technique, resulting in an SVM accuracy of 85.39% and a K-Means accuracy of 70.77%. Overall, these studies collectively emphasize the effectiveness of deep learning approaches in enhancing the detection and classification of ocular diseases.

In this study, we propose the use of ResNet-50 pre-training which is one of the transfer learning methods to create a classification model. The ResNet-50 pre-trained model offers superior accuracy compared to other techniques. Convolutional neural network (CNN) algorithms are widely recognized for their effectiveness in object detection and recognition tasks in image processing applications [15]. Therefore, this study adopts the ResNet-50 pre-trained model and applies fine-tuning to classify ocular diseases using retinal fundus images. The performance of ResNet-50 can be optimized by carefully selecting appropriate hyperparameters, which play a pivotal role in determining the model's overall performance. The accuracy achieved by ResNet-50 has been validated by previous studies [16]–[18]. The novelty of this research lies in the innovative application of the ResNet-50 method for the classification of retinal fundus images, coupled with fine-tuning specific parameters such as learning rate and patience. The classification outcomes will facilitate the categorization of data into four distinct groups: normal eyes, cataracts, glaucoma, and diabetic retinopathy. The primary objective of this study is to provide medical practitioners with a rapid and accurate framework for classifying ocular diseases, thereby effectively reducing the risk of blindness among affected individuals.

2. METHOD

This research paper introduces a methodology for the classification of ocular diseases utilizing retinal fundus images. The proposed architecture encompasses various stages, including data acquisition, data partitioning, data preprocessing, feature extraction, fine-tuning, prediction, and evaluation. The model's performance is assessed using accuracy metrics and compared with previous research results. The workflow of the study is illustrated in Figure 1.

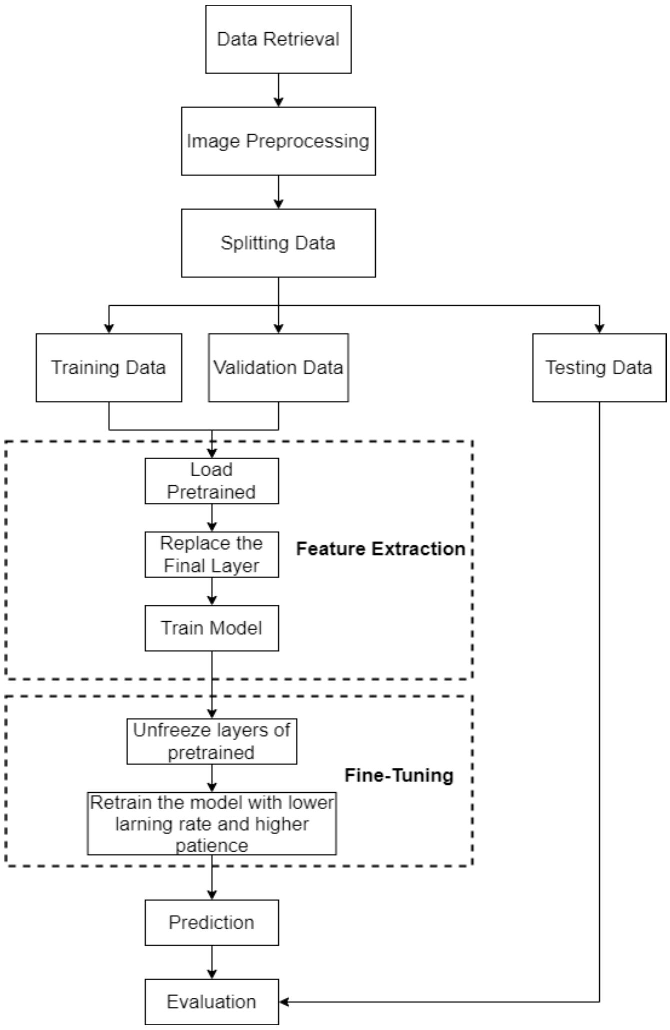

Figure 1. Research framework

2.1. Data retrieval

The dataset utilized in this research was collected from various reputable sources, namely the Indian diabetic retinopathy image dataset (IDRiD), ocular recognition, and the human rights foundation (HRF). It encompasses four distinct classes: normal, diabetic retinopathy, cataracts, and glaucoma. The dataset comprises a total of 4,217 retinal fundus images, with 1,038 images representing cataracts, 1,098 images depicting diabetic retinopathy, 1,007 images portraying glaucoma, and 1,074 images depicting normal retinas. This study made use of the entire dataset. The detailed distribution of the dataset can be observed in Figure 2, while Table 1 provides a comprehensive breakdown of the dataset allocation. Figure 2(a) displays normal retina fundus, Figure 2(b) shows retinal signs of diabetic retinopathy, Figure 2(c) presents retinal signs of cataract, and Figure 2(d) exhibits retinal signs of glaucoma.

Table 1. Dataset of visual impairments

No	Class	Number of images
1	Diabetic retinopathy	1,098
2	Cataracts	1,038
3	Glaucoma	1,007
4	Normal	1,074
Total		4,217

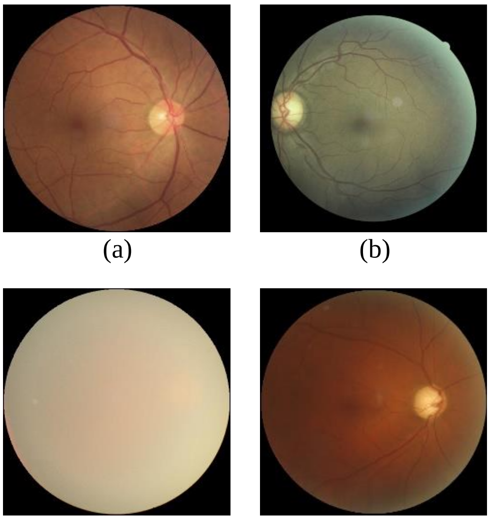

Figure 2. Retina fundus (a) normal, (b) diabetic retinopathy, (c) cataracts, and (d) glaucoma

The dataset was subsequently divided into three subsets to serve different purposes. It underwent data splitting, 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 was utilized for model development and training, enabling exploration of various parameter configurations to optimize the model's performance. The validation set was employed to assess and validate the trained models, while the testing set provided an independent evaluation to measure the final model's performance [19].

2.2. Preprocessing

Preprocessing involves transforming the data before utilizing it for model training, with the goal of enhancing the information content and strengthening the classification model [20]. In this dataset, which consisted of a total of 4,217 images across four classes, certain steps were taken to ensure uniformity and compatibility. The images were resized to dimensions of 224×224 pixels to establish a consistent size across the dataset. Additionally, normalization to the ImageNet format was performed, using mean values of [0.485, 0.456, 0.406] and standard deviations of [0.229, 0.224, 0.225]. It is important to note that no segmentation was conducted on the dataset.

2.3. Transfer learning

Transfer learning is a methodology that capitalizes on the knowledge acquired by a CNN from one dataset to address a distinct yet related task involving new data [21]. In medical-related research studies, the scarcity of medical data or datasets poses a significant challenge, despite the crucial role of data in deep learning approaches. Transfer learning provides a valuable advantage by mitigating the need for extensive datasets [22]. This approach leads to accelerated computational calculations and reduced costs. Specifically, transfer learning involves the utilization of a pre-trained model from a large dataset to initialize a new model that requires training, thereby requiring relatively smaller amounts of new data specific to the task at hand.

2.4. ResNet-50

ResNet stands out as one of the most widely employed convolutional neural network architectures, particularly in the context of ImageNet. It encompasses several configurations, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152 [23]. In the ImageNet large scale visual recognition challenge (ILSVRC) of 2015, ResNet was identified as the architecture with the lowest error rates. Notably, ResNet-50 is a prominent variant of ResNet, consisting of a total of 50 layers. This particular architecture is known for its ease of optimization, resulting in improved accuracy. Generally, ResNet-50 comprises five stages of convolutional processes, followed by average pooling and fully connected layers, which serve as the prediction layer. The underlying principle of ResNet involves constructing a deep network while simultaneously addressing the challenges of vanishing gradients and weight stagnation within the network [24]. This is achieved through the incorporation of residual layers and skip connections, which significantly contribute to enhanced accuracy.

The study conducted by Al-Moosawi and Khudeyer [25] highlights that ResNet-50 incorporates shortcut connections as an effective solution to prevent information loss during training. As the network depth increases, the issue of vanishing gradients arises, leading to reduced accuracy and performance. The introduction of shortcut connections in ResNet-50 aims to address this challenge by mitigating the loss of crucial information during the training process. By adhering to the conceptual framework and operational principles of ResNet-50, both accuracy and performance can be enhanced. ResNet-50 has gained recognition for its ability to improve the accuracy and performance of the resulting model, significantly impacting the precision of classification [13].

2.5. Training

The objective of the training process was to develop a convolutional neural network (CNN) model for the purpose of data classification. The obtained convolutional results were transformed into vectors and inputted into a fully connected layer of a neural network for classification. The study was conducted on Google cloud computing, which provided graphics processing unit (GPU) capabilities, enabling faster model training. To ensure consistent outcomes, a random seed value of 42 was assigned by the researcher to allow for reproducibility of experiments.

The LogSoftmax activation function was applied to the output layer, and the negative-log-likelihood (NLL) loss function was utilized as the loss function. Optimization was achieved using AdamW, and the EarlyStopping callback function was employed to halt the training process if the accuracy metric failed to improve within a specified patience threshold, indicating convergence. The patience value was set to 2 for the adaptation phase and 5 for the fine-tuning phase.

The adaptation process involved creating a CNN model from a pre-trained model, which was then utilized to classify the acquired dataset. During this process, the model was adapted to the available dataset, transformed into vectors, and passed through the neural network for classification. A learning rate of 0.001 was employed for the adaptation phase, while a learning rate of 1e-5 was used for the fine-tuning phase.

In the data preprocessing stage, the images were resized to dimensions of 224×224 and normalized to the ImageNet format for the training, validation, and testing data. For feature extraction, the researcher utilized pre-training on a large-scale ImageNet dataset, specifically using ResNet-50. The use of pre-training facilitated the research process by eliminating the need to train the feature extraction stage. This approach is commonly known as transfer learning. The necessary modification in transfer learning involved adjusting the architecture's head to align with the requirements of the dataset. In this case, the researcher employed four neurons in the output layer to accommodate the desired four-class classification.

2.6. Prediction and evaluation

Prediction is a data analysis process that effectively categorizes data into distinct groups. The quality of predictions depends on both the processed data and the constructed model, with superior training in classification model development leading to enhanced predictive performance. Evaluation is a crucial step in assessing the performance of the classification model [26]. Model evaluation involves using predictions generated from the testing data. To measure the effectiveness of the model, an accuracy metric is employed. This metric provides a comprehensive framework for evaluating the model's performance. The accuracy formula is represented by (1).

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

3. RESULTS AND DISCUSSION

The research employed the transfer learning method, specifically utilizing the ResNet-50 architecture and incorporating fine-tuning techniques. Transfer learning involves leveraging a pre-trained neural network model to address similar classification tasks by adapting it to the specific classification objectives. ResNet-50, a prominent architecture within the ResNet framework, was implemented using the PyTorch framework. The study utilized a dataset consisting of retinal fundus images, encompassing various conditions such as cataracts, diabetic retinopathy, glaucoma, and normal cases. By utilizing the ResNet-50 architecture, this study obtained an accuracy of 80.8%, after which fine tuning was carried out by reducing the value of the learning rate and also adding the patient value during training. After fine tuning the accuracy obtained increased to 92%.

This study employed a batch size of 64, which had a notable impact on the classification performance of the model. It was observed that a larger batch size led to poorer validation loss. Furthermore, a crop size of 224 was utilized to resize all image data to a standardized dimension of 224×224, enabling more efficient processing. The initial learning rate was set to 0.001, which was subsequently reduced to

0.00001 during the fine-tuning phase. The choice of learning rate value varied depending on the specific case, as higher values accelerated the training process but could compromise optimal learning, whereas lower values slowed down training but potentially yielded more optimal results. To ensure timely convergence, early stopping was implemented as a technique to halt the training process when the model no longer exhibited significant improvement. Initially, a patience value of 2 was set, but after fine-tuning, it was increased to 5. This indicated that if the model's performance did not improve within 5 epochs, the training process would be stopped.

In terms of methodology, a notable distinction can be made between this study and previous research efforts. For example, Ahmad and Hameed [11] conducted a study on visual impairments using the BPANN method and HMMD color space for feature extraction, achieving an accuracy of 85.26315%. Similarly, Verma *et al.* [14] focused on glaucoma detection using the SVM method, with K-means employed as a comparative technique, resulting in an SVM accuracy of 85.39% and a K-means accuracy of 70.77%. Furthermore, Bulut *et al.* [9] explored visual impairments utilizing the EfficientNet method, achieving an accuracy of 86%. In comparison, this study attained an accuracy of 92% using the ResNet-50 model on a dataset comprising cataract, diabetic retinopathy, glaucoma, and normal retinal images. A comprehensive overview of these comparisons can be found in Table 2. Based on Table 2, it can be observed that this research demonstrates better accuracy compared to the previous studies used as references.

Table 2. Performance of existing methods in comparison to this study

No	Researchers	Method	Accuracy
1.	Ahmed and Hameed	BPANN with HMMD color space feature extraction	85.26315%
2.	Verma *et al.*	SVM	85.39%
3.	Ahmad *et al.*	Hierarchal multi-label classification	75.7%
4.	Devi and Kumar	Gaussian blur and ResNet-50 without fine tuning	91%
5.	Bulut *et al.*	EfficientNet	86%
6.	Our study	Resnet-50 and fine-tuning	92%

4. CONCLUSION

Impaired vision can cause permanent blindness in sufferers if not diagnosed quickly and treated appropriately. Visual impairment is a prevalent condition affecting people worldwide, and its incidence is increasing daily. Cataracts, glaucoma, and diabetic retinopathy are well-recognized forms of visual impairments, affecting a staggering number of individuals, with at least 2.2 billion people worldwide experiencing some form of vision impairment. Fortunately, deep learning technology has shown great promise in effectively detecting these various visual disturbances. The proposed model in this study is trained using the ResNet-50 architecture, with fine-tuning techniques employed to enhance model performance. The results have demonstrated significant improvement, achieving an impressive accuracy of 92%, surpassing previous studies that utilized the EfficientNet model, which achieved an accuracy of 86%. Looking ahead, it is anticipated that the proposed model will become even more robust. In this study, the images were resized to smaller dimensions of 224×224 without performing any segmentation on the dataset. Therefore, it is important to investigate the potential impact of segmentation on the model's accuracy in future research. Furthermore, future versions of the proposed model are expected to encompass the detection of other types of visual impairments. To complete this research, the next step involves further exploration and development of a more efficient model. Additionally, the creation of a web-based or mobile-based application for diagnosing visual impairments using retinal images is a valuable direction for future work.

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