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Automated Classification of Ophthalmic Disorders Using Color Fundus Images

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Abstract
This study proposes a novel methodology for classifying ocular diseases using convolutional neural networks (CNNs) and specialized loss functions. The proposed model architecture incorporates a convolutional layer, global average pooling, ReLU activation, and novel loss functions (FL and CILF) to improve classification performance. The CNN architecture consists of three main layers: the convolutional layer (ConvL), global average pooling layer (GAPL), and fully connected layer (FCL). Trained on RFCI images with dimensions 299 x 299 x 3, the model effectively captures low-level features such as edges and curves, enhancing visual recognition capabilities. Convolutional operations are applied systematically across the entire image, with filters learning weights during training to extract relevant features. Experimental evaluation is conducted using two publicly available Ocular Health Dataset (OHD) datasets, comparing the proposed model with established baseline models (DenseNet-169, EfficientNet-B7, ResNet-101, Inception-V3, and VGG-19). Additionally, an ablation study is performed to assess the effectiveness of the proposed model. Results, averaged over three cross-validation tests, demonstrate the model's efficacy in classifying ocular diseases, particularly for categories such as CATR, AMD, and GLU.

Keywords: Ocular diseases, CNN, CATR, AMD , GLU , RFCI.

1. Introduction

In recent years, advancements in artificial intelligence have spurred technological innovations across various fields, including decision-making [1], medical diagnosis [2], clustering [3], and image segmentation [4]. This surge in AI capabilities has led academic researchers to delve into deep learning-based techniques for medical image segmentation. Medical images play a crucial role in medical research, clinical diagnosis, and pathological analysis, fueling both theoretical and technological progress in human medicine.

Among these medical images, fundus retinal vessels are of particular interest. These microvascular structures, located deep within the body, offer significant research value due to their non-invasive observability. Changes in the structure of these vessels, such as alterations in vascular diameter and curvature, are closely linked to the severity of conditions like diabetes, hypertension, and various blood disorders. By studying these changes, researchers can gain valuable insights into the progression and severity of these diseases, highlighting the importance of continued innovation in AI-driven medical imaging technologies.

Many challenges in the practical application of retinal vascular image segmentation algorithms in the fundus remain unresolved. In human physiology, the fundus retina is located in the innermost layer of the eye. Its spherical shape often results in clinical situations where only partial images are obtained, and the illumination is uneven. Traditional medical image segmentation methods, such as those based on thresholding, clustering, edge detection, and deformable models, face significant limitations regarding accuracy and the universality of images across different categories [5].DL is a subfield of machine learning (ML) that is finding increasing use in the field of medicine, namely in the analysis of RFCI. The severity of AMD was used by Meng et al. [6] to construct 13 different forms of AMD, and they built a classification method based on six common convolutional neural networks (CNNs) to assess the stage of AMD. Zekavat et al. [7] proposed the use of a transfer learning (TL) strategy to differentiate between the various phases of CATR. A convolutional neural network (CNN) and a support vector machine (SVM) classifier that has been pre-trained are the basis for this classification. After recruiting 21 ophthalmologists to diagnose GLU based on color fundus pictures, [7] examined the efficacy of an inception-based CNN model for detecting glaucomatous optic neuropathy. SVM and fully connected neural network (FCNN) were used by Yang et al. [8] to automatically extract relevant features and level six CATR. Wu et al. [9] developed a deconvolution network approach to investigate the procedure of global feature extraction. In addition to drawing attention to the significance of detailed information, this methodology also provides a CATR grading model that is founded on both global and local features. Faes et al. [10] developed a DL classification architecture by modeling it after the human grading process. As a result, they achieved a high level of accuracy in the detection

and prediction of AMD. Before determining the overall severity of the condition, the algorithm does a separate analysis of each of the AMD risk factors. The progression of AMD was predicted by Kanno et al. [11] using a DL system to analyze genetic information and visual data.
The goal of research is to build a suitable deep learning framework capable of accurately analyze ophthalmic disorder in various stages of diabetic retinopathy using color fundus images, providing precise diagnoses in early detection and intervention strategies, reducing the risk of vision loss and improving patient outcomes in diabetic retinopathy management.

2. Review of Literature

In this section, we will discuss about the various numerous diagnostic approaches that's mostly utilized at the moment of ophthalmic disorders related to diabetic retinopathy.
Amit Bhati et al. [12] proposed a novel approach with DKCNet, a convolutional network designed for analyzing retinal images to diagnose eye diseases and diabetic retinopathy. Their model, incorporating techniques like the DKC Block and ResNet backbone, aims to enhance multi-label classification accuracy and address dataset imbalances. The model achieved an AUC of 96.08 and an F1-Score of 94.28. Additionally, their hybrid model reached 79.56% accuracy for diabetic retinopathy, while DenseNet12 achieved 97.30% accuracy using the APTOS dataset.
Alwakid et al. [13]applied ESRGAN to enhance image quality, resulting in a classification accuracy of 98.7%. Without using CLAHE, the accuracy was 80.87%.
Lin et al [14] utilized a ResNet-50 model for diabetic retinopathy grading, with fundus images pre-processed using standard methods. The model achieved training and testing accuracies of 0.8395 and 0.7432, respectively.
Abdel Maksoud et al.[15] developed the E-DenseNet model to identify standard and diabetic retinopathy grades from fundus images, achieving accuracies of 91.6%, sensitivity of 95%, specificity of 95.1%, and a dice similarity coefficient of 0.92.
Raja Sarobin M et al. [16] proposed two hybrid models: CNN using ResNet, with an accuracy of 93.18% on a dataset of 3662 images, and CNN using DenseNet, with an accuracy of 96.22%.
Jabbar et al. [17] addressed the challenge of classifying medical images with limited labeled data by using transfer learning. Their VGGNet model for diabetic retinopathy classification achieved an accuracy rate of 96.6%.
Junjum He et al. [18] presented DCNet for patient-level multi-label ocular disease classification using color fundus photography. This model, featuring a backbone CNN and a spatial correlation model, demonstrated superior performance with lower computational complexity.
Elsharif et al. [19] diagnosed retinal diseases caused by Age-Related Macular Degeneration (AMD) and Diabetic Macular Edema (DEM) using deep learning and Optical Coherence Tomography. Techniques included VGG-16, MobileNet, ResNet-50, Inception V3, and Xception, with ResNet-50 achieving an accuracy of 96.21%.
Jing et al. [20] used deep learning to extract features from fundus images and machine learning for classification, working with an 8-label OHD dataset. They employed histogram equalization for preprocessing and tested two classification methods, averaging the probabilities to address data imbalance issues.
Fan et al. [21] presented a CNN model for glaucoma classification using fundus images, achieving an accuracy of 96.2%.
Dipu et al. [22] discovered eight ophthalmic disorders using transfer learning and the ODIR2019 dataset, evaluating the performance of models including ResNet-34, VGG-16, MobileNet-V2, and EfficientNet.
Yang et al. [23] developed a machine learning model using a two-class boosted decision tree for diabetic retinopathy detection, achieving an accuracy of 92.3% with Microsoft Machine Learning Studio.
Mayya et al. [24] designed a graph convolutional network (GCN) to identify eight types of diabetic retinopathy lesions in color fundus images, using ResNet-101 and XGBoost for feature extraction and classification, respectively, showing improved accuracy.

3. Materials and Methods

This section outlines the proposed methodology and criteria for evaluating the classification performance of the proposed model and baseline models.

3.1 Proposed Model

Figure 1 shows the general structure of the proposed model. It consists of a convolutional layer, global average pooling, ReLU activation, and the proposed loss functions: FL and CILF.

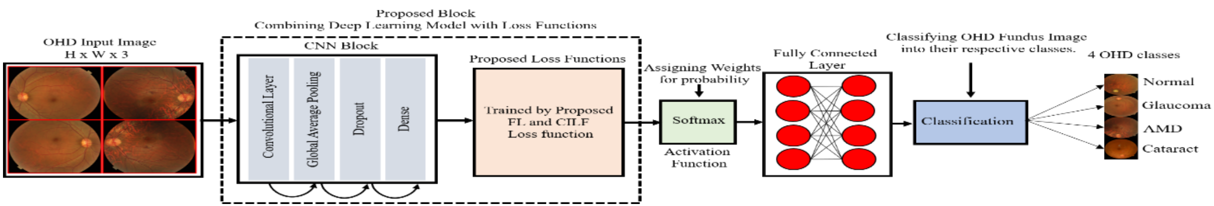

Figure 1. Proposed ODD Model

3.1.1 CNN Architecture

The proposed model uses a simple CNN network to extract features. This CNN has three main layers: the convolutional layer (ConvL), the global average pooling layer (GAPL), and the fully connected layer (FCL). The model is trained on RFCI images with a size of 299 x 299 x 3, where the number of channels (Cn) is three.

The first layer processed is the ConvL, which uses filters of size (3, 3), where both the height (IH) and width (IW) of the filter are 3. These filters, also called "kernels" or "feature identifiers," help the layer capture low-level features like edges and curves. Adding more ConvLs to the model improves its ability to extract deep features from RFCI images, enhancing its visual recognition capabilities.
During convolution, a filter is applied to a portion of the image, and element-by-element multiplication with the pixel values is performed, followed by summation. These values are known as weights or parameters, which the model learns during training. The portion of the image processed by the filter is called the "receptive field," and it is crucial for feature extraction. Convolution starts at the beginning of the RFCI image and is repeatedly applied across the entire image in a systematic manner.

4. Results and Discussions

This section presents the experimental results from two publicly available OHD datasets, comparing the proposed model with baseline models such as DenseNet-169, EfficientNet-B7, ResNet-101, Inception-V3, and VGG-19. An ablation study of the proposed model is also included.
We used two benchmark RFCI datasets for training and evaluation. The first dataset includes 601 RFCI images: 300 normal, 101 CATR, 100 GLU, and 100 AMD images. The second dataset, ODIR-2019, contains various OHD categories and includes 4020 reviewed cases out of an initial 5000.
RFCI images of OHD collected from two different datasets. The red dotted line represents the infected region of the eyes.

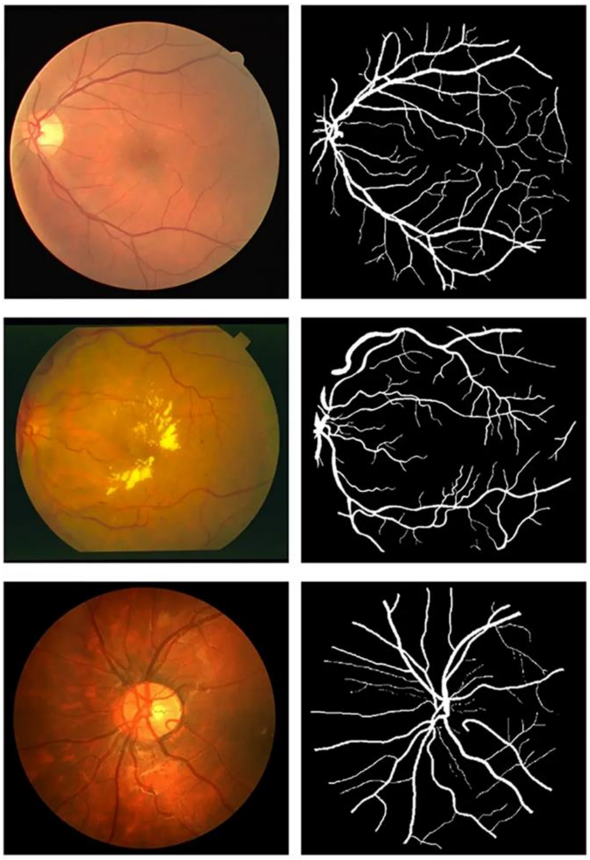

Figure 2: RFCI images of OHD

These RFCI images were used to evaluate our approach. Due to limited data, cross-validation was performed by training on two folds and testing on the third. To address class imbalance, we used the Tomek-SMOTE method, especially for minority classes like GLU, CATR, and AMD. The dataset, with and without Tomek-SMOTE, consists of 5300 examples: 530 for validation, 3710 for training, and 1060 for testing. Results are averaged over three cross-validation tests.
The results of the training and validation are presented in Table 1, which breaks down the results by epoch. The baseline models, and the proposed CNN model, were run for as many as 300 iterations. The highest level of accuracy that could be attained via training was 96.15%, while the highest level that could be reached through validation was 92.36%. These results suggested that the model learned well and was able to accurately classify GLU, CATR, and AMD in comparison to the baseline models.

Table 1: Results

Models	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
DenseNet-169	92.36%	0.17	90.01%	0.34
Proposed Model	96.15%	0.04	93.92%	0.03

4.1 Model Computational Complexities

Table 2 contains an in-depth analysis of the network's features, as well as information on its level of complexity and the number of floating-point operations performed per second. As a consequence of this, we are in a position to conduct an assessment of the outcomes of the categorization in a way that is not only just but also objective.

Table 2. Differences in computational complexities between a proposed model and baseline models.

Models	FLOPS	Parameters (Millions)
DenseNet-169	63.12	52.49
EfficientNet-B7	54.80	53.98
VGG-19	32.92	42.98
ResNet-101	54.74	42.38
Inception-V3	51.40	47.85
Proposed Model	23.21	32.79

5. Discussions

Deep Learning (DL) techniques have been utilized to aid in diagnosing the three leading causes of blindness: AMD, CATR, and GLU. In this study, we developed a novel DL model incorporating FL and CILF to classify OHD diseases. These loss functions address class imbalance and outliers in complex OHD datasets. The proposed model was trained on two publicly available RFCI datasets using fundus images and compared against several baseline models.

Our model outperformed the five baseline models, achieving a 96.15% accuracy and 93.92 validation accuracy. It effectively handled class imbalance using SMOTE-Tomek. While the model is well-suited for classifying CATR, AMD, and GLU, it is not suitable for other OHD diseases such as amblyopia, strabismus, and refractive errors.

6. Conclusion

This study presents a DL-based CAD model for classifying OHD images, utilizing a CNN combined with FL and CILF loss functions. The Tomek-SMOTE method was employed to address class imbalance. The model's performance was evaluated using two publicly available datasets, each containing four distinct OHD categories, achieving a classification accuracy of 96.15%.

Our method demonstrated superior classification accuracy, sensitivity, specificity, and AUC compared to other standard DL-based classifiers, largely due to the inclusion of the mixed loss function. The findings indicate that our proposed DL approach is both effective and robust for classifying ocular disorders. In the future, we aim to develop a federated learning-based collaborative model with the assistance of multiple hospitals, ensuring patient information confidentiality.

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