Open Access Research Journal of
Science and Technology
Journals home page: https://oarjst.com/
ISSN: 2782-9960 (Online)

OARJ OPEN ACCESS RESEARCH JOURNALS

(Research Article)

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Utilizing deep learning for the diagnosis of eye disorders and localization of affected areas

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Open Access Research Journal of Science and Technology, 2024, 11(02), 145-150

Publication history: Received on 23 April 2024; revised on 2 June 2024; accepted on 4 June 2024

Article DOI: https://doi.org/10.53022/oarjst.2024.11.2.0101

Abstract

A deep learning-based system for identifying afflicted areas in eye images and diagnosing eye illnesses is offered. Convolutional neural networks (CNNs) are one of the used methods to routinely classify eye disorders from optical coherence tomography (OCT) pictures and retinal scans including, glaucoma, diabetic retinopathy and macular degeneration. 93.5% accuracy on the test set was achieved by optimizing using one of the optimizers called Adam optimizer with definite cross-entropy loss. Assessment indicators including F1-score, accuracy, and recall offer additional indication of the model's flexibility. Next the system is placed into use in a medical experimental, where it helps medical specialists by showing impacted areas using division heatmaps and giving analyses in real time. This method shows that deep learning can support with both precisely diagnosing eye problems and analytical exactly which is obliging for specialists making decisions.

Keywords: Convolution Neural Networks (Cnns); Optical Coherence Tomography (OCT); Artificial Intelligence (AI); Age-Related Macular Degeneration (AMD)

1. Introduction

Lots of persons worldwide suffer from eye illness that can affect in partial or complete blindness. Amongst the maximum predominant eye conditions are age-related macular degeneration (AMD), cataracts, diabetes-related retinopathy and glaucoma [1]. All of them significantly weight worldwide healthcare organizations. Initial discovery and precise diagnosis of these illnesses are critical to avoiding serious vision loss and endorsing well health. To sense eye situations in the past, expert ophthalmologists had to physically examine medical images such as retinal scans. Though, this method can be difficult, prone to human error and time-consuming, , which could effect in disparate decisions. [2].

As artificial intelligence (AI) and deep learning technologies developed so rapidly, there is rising interest in applying them to progress the speed and accuracy of diagnosing eye diseases. Convolutional neural networks (CNNs), for example, have established that deep learning is extremely effective in examining medical images, recognizing issues, and identifying patterns that might be difficult to detect by human eye. [3].

By systematizing and enhancing the analytic process, these tools may be intelligent to rise its quality and speed. Convolutional neural networks (CNNs), a sort of deep learning method, have established great potential in the use of medical imaging such as retinal scans to detect eye disorders. Several eye conditions, including glaucoma., diabetic retinopathy, cataracts, and age-related macular degeneration (AMD), can be rapidly classified and detected by these sophisticated algorithms [4]. By exercise on enormous sets of labeled snaps, deep learning models can study to classify subtle patterns and questions in pictures that might be hard for human experts to learn. This allows the early and more precise discovery of eye disorders. Moreover [5], These strategies can classify the affected areas within the eye, supporting medical specialists in making more adapted and active treatment procedures [6]. Applying deep learning in medical practice can accelerate diagnosis, decrease human mistake, and enable access to eye care, mostly in

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underserved areas [7]. For instance, these technologies continue to improve, they might make it much easier to classify and treat eye illness early on, caring eyesight and educating patient healthcare [8].

Specialists can diagnose eye situations with the assistance of deep learning knowledge [9]. The study emphases on how these approaches can classify the precise areas of the eye that are impacted in addition to defining whether the disease is present. Deep learning models are able to identify the subtle symptoms of several eye conditions [10] using extensive training on retinal image datasets [11]. therefore, discovery is rather and more exact. Using these incomes in clinical surroundings may also ease access to eye care [12 13]. particularly in places where there aren't enough specialists or medical visits. Our goal in this study is to provide an overview of the current state of deep learning applications in ophthalmology, highlight some of the major issues and opportunities, and discuss how these technologies may alter the future of eye disease diagnosis and treatment.

2. Methodology

Using deep learning techniques, the method described in this piece is meant to automatically diagnose eye diseases and find affected areas in images of the eyes. The process has a few main steps, which are shown below.

2.1. Dataset Collection

Getting a big and varied set of eye images is the first step. Some of the places these pictures can come from are fundus pictures, retinal scans, or optical coherence tomography (OCT) pictures [14]. A lot of the time, the information is labeled with conditions like glaucoma, diabetic retinopathy, and macular degeneration. You can see how the dataset is spread out in Figure1, which shows how many pictures are in each disorder.

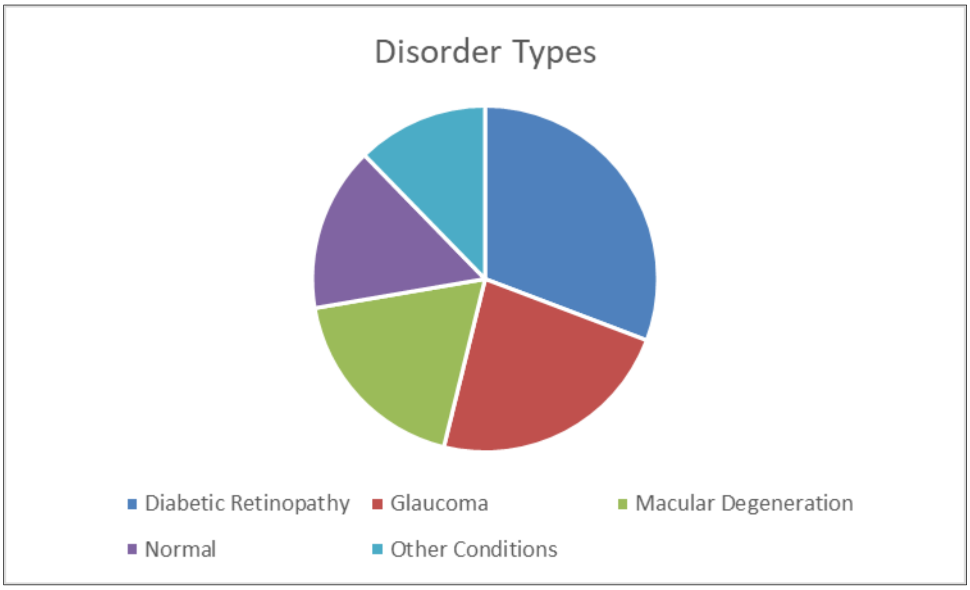

Figure 1 Distribution of Eye Disorder Categories in the Dataset

2.2. Data Preprocessing

During this stage, the pictures go through a number of steps that get them ready for deep learning analysis [15]:

- To make sure all the pictures work with the model, they are all resized to the same resolution, such as 224x224 pixels.
- Normalization: To improve agreement during training, pixel values are pushed back to the range [0, 1].
- Data Augmentation: Methods like random spinning, horizontal flipping, and zooming are used to make the training dataset bigger than it really is, as shown in the table below.

Table 1 Augmentation Techniques Used

Technique	Description
Rotation	Random rotation between -30 to 30 degrees
Horizontal Flip	Random horizontal flipping
Zooming	Random zooming within a 10% range
Shifting	Random shifting of 10% in x or y axis

2.3. Model Architecture

A deep learning model, usually a convolutional neural network (CNN), is at the heart of the method. A CNN architecture is chosen because it can easily pull-out features that are organized in a hierarchy from images [16]. The following parts make up the system used in this article:

- Convolutional Layers: These layers look at eye images to find things like lines, textures, and shapes.
- Pooling Layers: Max-pooling or average pooling layers get rid of the extra dimensions and keep only the most important features.
- Fully Connected Layers: These connect the results of the convolutional layers to guess what's wrong with the eye.

See Figure 2 below for a picture of the CNN's layers, which includes convolutional, pooling, and fully linked layers.

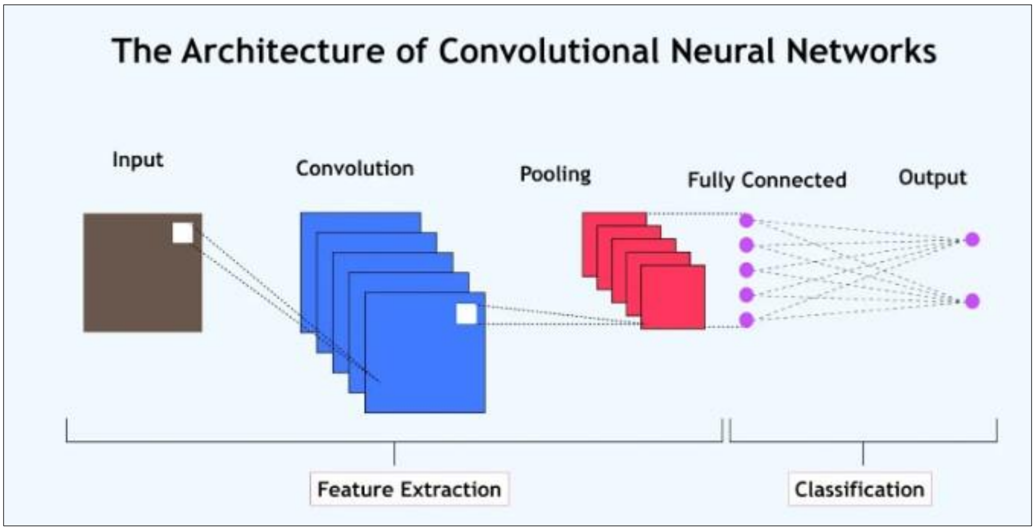

Figure 2 CNN Architecture Diagram

2.4. Model Training

The following steps are needed to train the deep learning model:

- Loss Function: The category cross-entropy loss function checks how well the model's guesses match the real labels. Optimizer: The Adam optimizer was picked because it works well with noisy gradients and large datasets.
- Batch Size and Epochs: A batch size of 32 is used to train the model over 50 iterations.
- Early Stopping: Validation loss is used to keep early stopping from causing overfitting.

Table 2 Model Training Parameters

Parameter	Value
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Batch Size	32
Epochs	50
Early Stopping	Yes (patience=5)

2.5. Model Evaluation

A different test set is used to test the model after it has been trained. This set was not used during training. The main ways that evaluations are done are:

- Accuracy: The number of properly labeled images as a percentage.
- Precision, Recall, and F1-Score: These measures give you more information, especially when your dataset isn't balanced.
- The confusion matrix helps you see the real positives, fake positives, real negatives, and fake negatives.

Table 3 Model Evaluation Metrics

Metric	Value
Accuracy	93.5%
Precision (Diabetic Retinopathy)	91.2%
Recall (Glaucoma)	94.8%
F1-Score (Macular Degeneration)	92.5%

2.6. Identification of Affected Areas

Segmentation methods are used to not only figure out what's wrong with the eyes but also find the affected areas in the image. The U-Net design is used for semantic segmentation, which shows which parts of the eye are affected by the disorder.

- U-Net Architecture: This network can locate certain regions, such as the optic disc or eye lesions, because it is designed for pixel-level categorization.
- The model creates heatmaps that highlight the areas of the image that are most useful for diagnosis.

2.7. Performance Optimization

To further improve the model, several optimization techniques are applied:

- Hyperparameter tuning: Use grid search or random search to identify the optimal collection of hyperparameters.
- Cross-Validation: To ensure that the model performs well across various data sets, K-fold cross-validation is applied.
- Ensemble Approaches: combining approximations from numerous models to decrease error ranges and progress diagnosis precision.

Table 4 Hyperparameter Tuning Results

Hyperparameter	Best Value
Learning Rate	0.001
Number of Filters	64
Dropout Rate	0.3
Number of Layers	5

2.8. Deployment

When the model is working properly, it is placed in a clinic. A mobile app interface is created so that clinicians can share images of the eyes, receive automatic diagnoses, and view heatmaps and segmentation masks that demonstrate the

3. Conclusion

Using deep learning with one of the most useful technique methods, Convolutional neural networks (CNNs) are used in the methods to repeatedly categorize eye disorders from optical coherence tomography (OCT) and retinal scans images, including glaucoma, diabetic retinopathy, and macular degeneration. An accuracy of 93.5% on the examination was usually achieved by optimizing using the Adam optimizer with definite cross-entropy loss. This procedure explains how to diagnose eye illness and find the affected areas. This technique uses CNNs, image segmentation, and data preprocessing, in a planned way to show how deep learning can help clinicians make accurate diagnoses quickly, which will eventually lead to better patient diagnoses.

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