EyeVision: Deep Learning-based Image Classification for Eye Conditions

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Abstract

Eye diseases, such as cataract, diabetic retinopathy, glaucoma, and normal fundus, pose significant challenges for timely and accurate diagnosis. Leveraging deep learning, specifically Convolutional Neural Networks (CNN), this project aims to assist ophthalmologists in diagnosing these conditions more effectively by processing retinal images and classifying the diseases based on extracted features. A vital tool used in the performance assessment of this classifier is the confusion matrix, which measures the performance on individual classes, offering insights into how well the model distinguishes between various conditions. While not exclusive to neural networks, the confusion matrix applies to any classification algorithm and provides critical metrics to improve model accuracy. This project utilizes a confusion matrix to evaluate the model's predictive ability and identifies which diseases the model struggles to classify correctly. By combining CNN with this evaluation method, the system enables better diagnostic support, promoting faster and more precise treatment recommendations for patients.

1 Introduction

In the modern age of medical advancements, the accurate and timely diagnosis of eye diseases remains a critical challenge, especially in cases where visual symptoms can be subtle or hard to detect. Eye diseases often present with varying textures, making manual diagnosis by optometrists prone to error. To address this, artificial intelligence, specifically deep learning models like CNNs, are being employed to automate and improve diagnostic accuracy. One important performance measurement technique used in classification tasks is the confusion matrix. Although not specific to neural networks, it provides a detailed breakdown of how well a model classifies individual classes in a dataset. The matrix, based on the test set with known true labels, fills a table comparing predicted labels versus true labels. This matrix gives a clear idea of how accurate the classifier's outcomes are and allows developers to identify which areas need improvement. Confusion matrices, when applied to CNN models, offer insights into the classifier's strengths and weaknesses in distinguishing between different eye conditions, ensuring high levels of accuracy and performance. This project, EyeVision, introduces a CNN-based approach to classify images of cataract, diabetic retinopathy, glaucoma, and normal eye conditions. Utilizing a confusion matrix, it evaluates the performance of the model and highlights areas where classification can be improved.

2 Problem Formulation

Eye diseases can manifest in many forms, and their textural differences are sometimes difficult to identify, even for experienced optometrists. Using artificial intelligence and deep learning to enhance current diagnostic systems offers significant advantages, improving the speed and accuracy of diagnosis and making healthcare more efficient. This paper uses a confusion matrix to evaluate the performance of CNN architectures in classifying eye diseases. Specifically, it identifies which diseases the model struggles to classify correctly, providing insights for further improvements in accuracy.

3 Related Work

Several researchers have contributed to the field of machine learning and neural networks for image classification, with many focusing on improving accuracy through various evaluation techniques, including confusion matrices.

1. Labatut, Vincent, and Hocine Cherifi : The authors reviewed performance measures for comparing classifiers, particularly emphasizing the importance of using simple, interpretable measures like TPR and PPV. They discussed the theoretical differences in accuracy measurement and recommended choosing simple measures for performance evaluation.
2. Visa, Sofia, et al. : The authors proposed a confusion matrix-based feature selection method. This approach selects features based on classification accuracy and subgroup complementarity, allowing better model performance through optimized feature subsets.
3. Nezami, Omid Mohamad, et al. : Their work presented a deep learning-based engagement recognition system using pre-trained facial expression data to improve engagement prediction accuracy.
4. Loussaief, Sehla, and Afef Abdelkrim : This paper focused on machine learning techniques for image classification, evaluating models using confusion matrices and proving the effectiveness of the SURF feature extractor for image classification tasks.
5. Bizios, Dimitrios, et al. : The authors compared machine learning classifiers, specifically support vector machines and artificial neural networks, for glaucoma diagnosis. They found that input parameters have a more significant effect on diagnostic accuracy than the type of classifier used.

4 Data Description

The dataset used for this project consists of retinal images from four different categories:

- Cataract: 1024 images

- Diabetic Retinopathy: 1101 images
- Glaucoma: 1007 images
- Normal Fundus: 1074 images

Each of these categories represents different eye conditions, and the CNN model is trained to classify images from these categories.

5 Methodology

The CNN model developed in this project follows a typical architecture, consisting of three convolutional layers, each followed by max-pooling layers, and two fully connected layers. The input images are resized to 224x224 pixels, normalized, and passed through the network for feature extraction. The final output layer contains four neurons representing the four different eye conditions. To evaluate the performance of the model, the confusion matrix is used. This matrix enables a detailed analysis of which classes are correctly classified and where the model may be confused. In particular, it helps identify misclassifications, such as diabetic retinopathy being mistaken for glaucoma. Through this analysis, the model is fine-tuned to improve accuracy. The dataset is split into training, validation, and testing sets, and the model is trained over 10 epochs using the Adam optimizer. The test accuracy of the model is 93.36, indicating high classification performance, though further improvements are possible by fine-tuning the model based on confusion matrix analysis.

6 Conclusion

The EyeVision system, based on CNN, demonstrates effective classification of common eye conditions, with a test accuracy of over 93 percentage. The use of the confusion matrix has been crucial in understanding the performance of the model on each class, offering insights for further optimization. This deep learning-based approach can serve as a powerful tool in assisting ophthalmologists with timely and accurate diagnostic recommendations.

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