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A Survey On Deep Learning Applications For The Classification Of Eye Diseases

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Abstract: Recent studies demonstrate the growing role of deep neural networks in the automated detection of prominent ocular diseases such as glaucoma, diabetic retinopathy, and cataract. This review examines existing research that applies deep learning techniques to retinal and ocular image analysis for diagnosis and classification of the three fatal diseases: cataract, glaucoma and diabetic retinopathy. Prior works are analyzed in terms of network architectures, imaging modalities, preprocessing methods, and prominent evaluation strategies. The review highlights consistent improvements in diagnostic accuracy achieved through convolutional neural networks and transfer learning approaches. It also reviews the publicly available dataset for cataract, glaucoma and diabetic retinopathy. This review aims to provide insights into current advancements applicable to deep learning–based ophthalmic diagnostic systems.

***Index Terms* -** Glaucoma, Diabetic retinopathy, Cataract, Disease classification.

I. INTRODUCTION

Worldwide, eye diseases pose a major public health challenge, with cataract remaining the leading cause of blindness affecting tens of millions of people, glaucoma impacting over 70 million individuals, and diabetic retinopathy emerging as a significant cause of vision impairment among the rapidly growing diabetic population. These eye conditions often develop gradually and may not cause noticeable symptoms in their early stages, allowing damage to progress unnoticed. Glaucoma can silently destroy the optic nerve, cataracts slowly cloud the lens and reduce visual clarity, and diabetic retinopathy damages retinal blood vessels due to prolonged high blood sugar levels. When identified early through regular eye examinations, effective treatments and lifestyle interventions can slow disease progression, preserve remaining vision, and improve long-term visual outcomes. Timely diagnosis also reduces the social, economic, and personal burden associated with advanced vision impairment, highlighting the importance of routine eye care, especially for high-risk individuals.

Cataract is a progressive disease that causes gradual clouding of the eye lens, generally found in people aged over 40. The underlying reasons for cataract include the most common causes of ageing, genetics, diabetes, eye injuries, poor nutrition and long-term use of certain medications [1]. It can be categorized according to the developmental stages. Researchers have applied different eye images for cataract classification, such as slit lamp image, retro illumination image, ultrasonic image, fundus image, digital camera image, and anterior segment optical coherence tomography (AS-OCT) [2]. Figure 1 shows retinal fundus images of various stages of cataract [2].

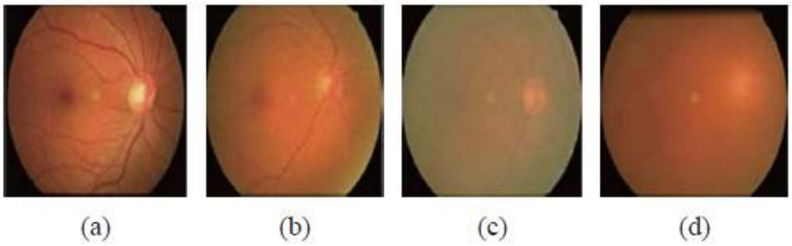

Figure 1: Retinal fundus images (a) Normal (b) Mild (c) Moderate(d) Severe

Glaucoma is an eye disease that causes progressive damage to the optic nerve, the structure that carries visual information from the eye to the brain [4]. The disease typically does not show any initial symptoms. The most common cause is the increased eye pressure, which damages the optic nerve. There are also other factors such as genetic history, eye injury, high blood pressure, and diabetes. Manual diagnosis of Glaucoma is challenging and requires the service of an expert ophthalmologist. If left untreated, it may lead to permanent blindness.

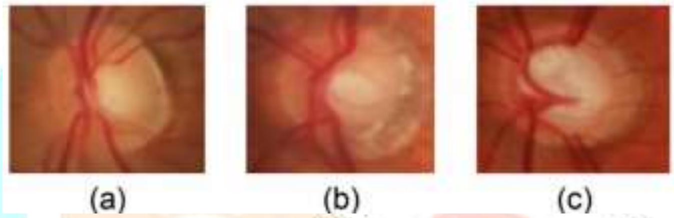

Figure 2: Retinal fundus images of Glaucoma (a) Normal (b) Early stage (c) Advanced stage

Diabetic retinopathy (DR) is a chronic eye disorder that results from hyperglycemia. Prolonged hyperglycemia leads to retinal vascular damage, resulting in complications such as microaneurysms and hemorrhages that lead to irreversible blindness. The early stages of DR is called non-proliferative DR (NPDR), and the advanced stage is called proliferative DR (PDR) [5]. The NPDR progresses through mild, moderate and severe stages. DR diagnosed at the stages of NPDR can be controlled from progressing to PDR. Figure 3 shows the progressive stages of DR.

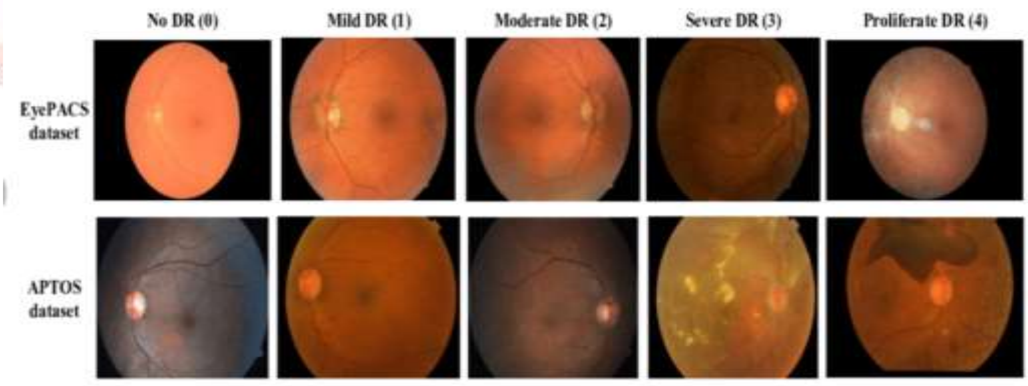

Figure 3: Different stages of DR retinal fundus images in EyePACS and APTOS datasets

Early identification of diabetic retinopathy, glaucoma, and cataract is essential for preventing long-term visual impairment, as these conditions often develop gradually without noticeable symptoms. Detecting diabetic retinopathy in its initial stages allows early medical intervention to slow disease progression and protect retinal health. Similarly, recognizing glaucoma early helps prevent irreversible optic nerve damage through timely pressure management, while early diagnosis of cataracts supports appropriate treatment planning to restore visual clarity. Deep learning enhances early detection by automatically analyzing retinal and ocular images with high precision, identifying minute abnormalities that may escape human observation. By enabling faster, scalable, and consistent screening, deep learning technologies support clinicians in making accurate diagnoses, expand access to eye care services, and play a significant role in reducing avoidable vision loss worldwide. Manual identification of eye diseases such as diabetic retinopathy, glaucoma, and cataract faces several practical challenges. The diagnostic process relies heavily on the clinician's skill and judgment, which can lead to inconsistencies and subjective interpretations. Early pathological changes are often faint and difficult to distinguish, increasing the risk of missed or delayed diagnoses. Manual screening also requires considerable time and effort, making it inefficient for large-scale population screening. In addition, the limited availability of trained specialists, particularly in rural and underserved areas, restricts timely access to eye care. Factors such as clinician fatigue and workload further contribute to diagnostic errors, allowing disease progression that may result in permanent vision loss. Recently, many researchers have applied deep neural networks for disease identification [6-8] and have reported better performance.

II. OCULAR IMAGING MODALITIES

Deep neural network–based studies in retinal analysis predominantly rely on fundus photography and optical coherence tomography (OCT), as these modalities offer a strong combination of clinical importance and accessible data resources [9], [10]. Fundus images are extensively used in automated screening and disease grading tasks because their planar representation aligns well with convolutional learning frameworks [11], [12]. OCT has similarly attracted considerable research attention, owing to its ability to capture detailed structural information of retinal layers, which supports advanced DNN applications such as tissue segmentation and pathological feature identification [13], [14]. The preference for fundus photography and OCT in DNN research largely stems from their practicality, richness of information, and established role in clinical workflows.

III. RETINAL IMAGE DATABASES

The availability of databases in public repositories is significant for studies based on DNN. Benchmark public datasets is necessary for reproducible research, fair performance comparison among algorithms, and training of robust models. There are several private and public datasets available on various ocular diseases. Table 1 presents a brief description of major publicly available datasets on the three diseases.

Table 1: Datasets of eye disease images

Database	**Number of images**	**Disease**
ODiR[15]	10,000	Multi-disease
Messidor [16]	1, 200	DR
Kaggle EyePACS [17]	80,000	DR
Kaggle APTOS[18]	5,000	DR
ACRIMA [19]	705	Glaucoma
ORIGA[20]	650	Glaucoma
Kaggle Cataract[21]	600	Cataract

IV. METHODOLOGY

The general structure of a deep neural network-based classification system, which is presented in most of the studies, is shown in Figure 4. The system typically starts with the collection of retinal images obtained from standard ocular imaging modalities. These images are often characterised by uneven lighting, low contrast, variable brightness, irrelevant background details and noise. This often results in the extraction of features with inadequate and improper details for DR evaluation. To overcome these challenges, pre-processing techniques are often applied to enhance significant image features for the classification. Techniques such as thresholding, filtering, noise removal and contrast enhancement are commonly used. The pre-processed images are then fed into the deep neural network to extract micro- and macro-level features. A deep neural network (DNN) is typically organised as a stack of layers, with each layer comprising hundreds of neurons. There are three types of layers in a typical DNN: An input layer that receives the pre-processed input data, several intermediate hidden layers that learn the data patterns, where the early layers learn simple patterns while deep layers learn complex input patterns, and the last output layer that calculate the final prediction. The performance parameters are calculated from the confusion matrix generated from the output layer.

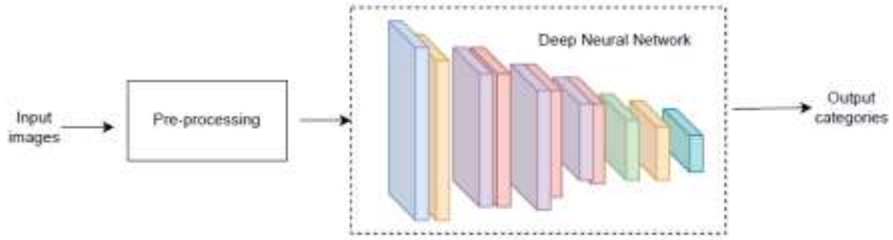

Figure 4: Schematic diagram of DNN based disease classification system

To enhance the robustness of the model, data augmentation strategies are often employed to increase variability and mitigate class imbalance. During training, the network parameters are optimized using labelled samples and suitable loss functions to minimize classification error.

V. RELATED WORK

Literature shows many studies on the detection and classification of cataract, glaucoma, and diabetic retinopathy. Most of these studies are based on DNN. This section reviews recent deep neural network (DNN)-based works on each of these diseases.

Yadav et al. [22] proposed a methodology in which images after pre-processing are transformed using 2D-DFT and applied to a convolutional neural network (CNN) model, and the retinal fundus images of cataract disease are classified into four categories according to the severity level of the disease. The authors reported an accuracy of 93.1%. Suryawanshi et al [23] applied YOLOv9 deep learning model for the detection and classification of cataract. Shantharaja et al [24] proposed a hybrid model consisting of both conventional and deep learning algorithms for cataract disease classification. The authors extracted features using Ineption V3 -based deep model and classified the features using SVM classifier.

Yadahalli et al. [25] classified retinal fundus images of different stages of Glaucoma disease using bilateral U-Net odel achieved a highest accuracy of 92.4% on DRISHTI-GS dataset. Dhanuja et al [26] proposed a new hybrid deep learning model, GlaucoLightNet, for Glaucoma disease classification and reported an accuracy of 94.5% on the REFUGE dataset. Guntreddi et al [27] classified Glaucoma images using an ensemble deep learning model and achieved an accuracy of 82.4%.

There are several studies on the classification of DR using deep learning algorithms. Hannan et al. [28] classified retinal fundus images of different stages of DR using DenseNet 169- based model enhanced by an attention network and achieved an accuracy of 83.2%. Hariobulesu et al [29] proposed a hybrid model for the classification of DR images where, after pre-processing, images are transformed using DWT and LBP. The resulting images are applied to U-Net based deep learning model, and the extracted features are classified using SVM classifier. The authors reported an accuracy of 98.7% on the Messidor-2 dataset.

From the review of recent works on the classification of ocular diseases, it is observed that most of the researchers have applied CNN-based algorithms. The transfer learning technique is widely used, and most of the pretrained networks are trained with the ImageNet dataset. Few studies show the application of hybrid models that use both conventional methods and deep learning algorithms, and achieve better performance.

VI. PERFORMANCE PARAMETERS

The efficacy of an image classification algorithm is analyzed using performance parameters. Although there are many performance parameters, the commonly used measurements are accuracy, precision, sensitivity, and specificity [30]. The reliability of a classifier can be determined by computing correctly the recognized class samples count (true positives-TP), correctly recognized non-class samples count (true negatives-TN), count of non-class samples wrongly assigned as class samples (false positives-FP) and count of class samples not recognized (false negatives-FN), which are obtained from the confusion matrix. The performance parameters are directly calculated from the values generated in the confusion matrix. The mathematical formulae for the calculation of these metrics are given below

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

$$Preision = \frac{TP}{TP + FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + TP} \quad (4)$$

$$F1 - Sore = 2\frac{Precision\ x\ Sensitivity}{Precision + Sensitivity} \quad (5)$$

VII. CONCLUSION

Diabetic retinopathy, glaucoma, and cataract are important diseases affecting the eye. Early diagnosis and medication are necessary to prevent diseases from progressing to an irreversible disorder. This paper presents a brief review of the literature on the application of deep learning algorithms for disease classification. The surveyed literature demonstrates that DNN models are capable of extracting intricate features from ocular images, enabling accurate identification of various eye conditions and outperforming many conventional classification approaches. While the reported results highlight the effectiveness of deep learning in improving diagnostic precision and supporting early disease detection, several limitations remain evident. Issues such as dataset imbalance, dependence on large annotated datasets, reduced transparency of decision-making processes, and variability in performance across different imaging sources continue to restrict widespread clinical adoption. In conclusion, deep neural networks represent a promising direction for eye disease classification and have the potential to significantly enhance clinical decision support systems. Future work should prioritize the development of interpretable models, improved data diversity, and rigorous clinical validation to ensure reliability and generalizability in real-world healthcare settings.

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