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Cataract classification based on traditional data augmentation methods: Review study

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ABSTRACT

Cataract is a major cause of visual impairment and blindness worldwide. This has led to the design of automated systems for early detection through retinal fundus imaging. Recently, deep learning techniques with a focus on CNNs have shown good results for cataract classification. However, the results obtained from these models are often limited due to the inherent class imbalance problem in most medical image classification problems. To overcome the class imbalance problem, several researchers have adopted traditional data augmentation techniques to increase the number of the minority class. This review aims to highlight the recent studies that have adopted traditional data augmentation techniques for the classification of cataracts. It presents an overview of the recent research trends for the classification of cataracts using traditional data augmentation techniques.

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1. Introduction

Cataract continues to be a major public health concern due to its strong association with vision impairment, its causes clouding of the natural lens of the eye, making the vision blurry and sensitive to light[1] [2]. Although cataracts are commonly associated with aging, they may also result from genetic factors, trauma, or certain medical

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conditions [3], because it develops in an unnoticeable way, the patient can reach an advanced stage if not examined early, which is why early detection is important to prevent reaching blindness[4].

Traditional diagnosis of cataracts relies on clinical eye examinations performed by trained specialists using slit-lamp imaging or fundus photography[5]. However, access to this specialized care is limited in many regions. This challenge has encouraged researchers to investigate more accessible solutions that can help in early detection[6].

Medical images have become an essential part of the present medical diagnostic process by providing a non-invasive technique for the visualization of internal body structures and facilitating the detection of diseases. Recent studies have shown that the inclusion of image-based information with other clinical data can improve the performance of the machine learning models[7] [8] [9]. This highlights the importance of image data that can be combined with other modalities for the development of effective decision-making systems [10], [11]. This is particularly relevant in the field of ophthalmology, in which the visualization of the retina by fundus images is a common technique for the detection of eye diseases such as cataract, glaucoma, and diabetic retinopathy[12], [13], [14].

In this context, artificial intelligence, especially deep learning (DL), has become a transformative engine in ophthalmology. Convolutional neural networks (CNNs) have shown satisfactory results in analyzing fundus images to classify various eye diseases[15], [16], [17]. These models are capable of learning complex patterns associated with disease features, enabling them to provide rapid diagnostic prediction [18], However building reliable deep learning model depending heavily on the availability of large and balanced datasets, which is often challenging in medical Imagin applications[19].

Class imbalance is considered to be a significant problem in the classification of medical images, which may cause bias in the model towards the majority class and reduce the sensitivity of the model[20], [21]. To address the problem, researchers have adopted traditional data augmentation techniques to address this issue. These techniques can be broadly categorized into geometric and photometric variations, which simulate real-world acquisition variations[22], [23]. including image flipping[24], rotation[25], and cropping[26], leading to increase in dataset size and reduce the risk of overfitting. While also improving the model's generalization capability. Many studies utilized these traditional augmentation techniques to develop cataract classification systems based on fundus images[27]. These studies have differed in methodology, model architecture, augmentation scope, and reported results, making it useful to study them collectively.

This paper explores and analyzes recent studies that have applied traditional data augmentation strategies to cataract classification. By highlighting different approaches, evaluation metrics, and key results, this paper provides a comprehensive overview of current progress in this field and offers insights into effective practices for training robust AI models in the field of ocular image analysis

2. Traditional Data Augmentation

Data augmentation is a fundamental strategy employed to training deep learning models, especially in the medical imaging filed. Collecting large, well-annotated datasets remains both challenging and expensive[28]. Traditional augmentation methods rely on applying a set of simple and direct geometric and photometric techniques to the original images. The goal is to artificially increase the volume of training samples within a given category without the need to collect new clinical images[25]. By exposing the model to these techniques during training, traditional augmentation enhances the diversity of the dataset and reduce the risk if overfitting[24]. Some of these methods include:

1. **Rotation** is a geometric data augmentation involve rotating an image by a specified or random angle while preserving its class label, thus contributing to the improved robustness of the model to orientation variations.[24], [29]. An example of the rotation technique is illustrated in Fig 2.1.

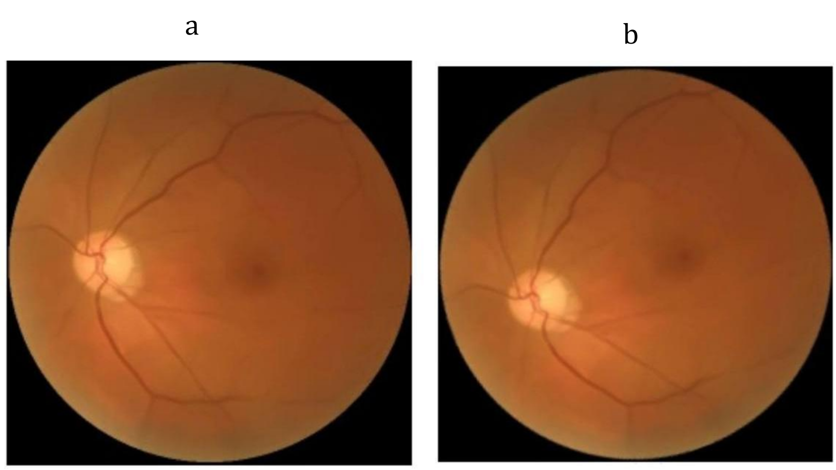

Fig.1 (a) Original fundus image, (b) Rotated fundus image.

2. **Flipping** is used to produce mirrored versions of an image along the horizontal or vertical axis. increasing data diversity without altering the label of the original image.[24], [29].An example of the flipping technique is illustrated in Fig 2.2.

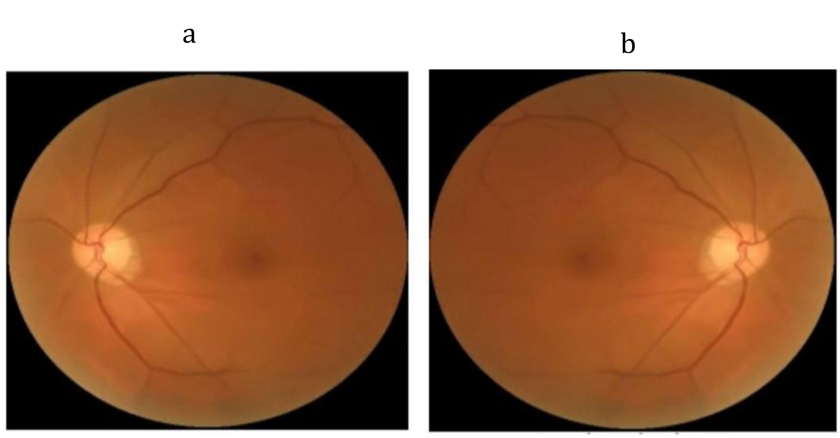

Fig .2 (a) Original fundus image, (b) flipped fundus image.

3. **Cropping** involves selecting a particular or randomly chosen area of the image and resizing it to the required size for input into the model.[26]. An example of the cropping technique is illustrated in Fig 2.3.

a b

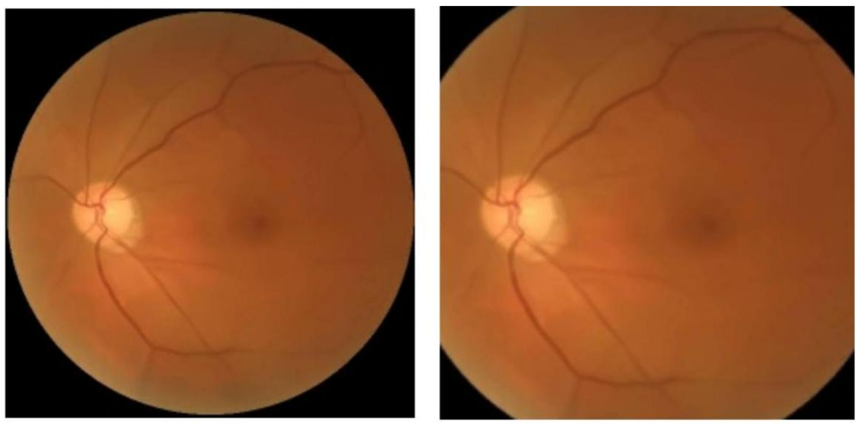

Fig .3 (a) Original fundus image, (b) cropped fundus image.

4. **Translation** involves shifting the image along one direction. Thus, translation helps the model to learn features regardless of their location.[26].An example of the translation technique is illustrated in Fig 2.4.

a b

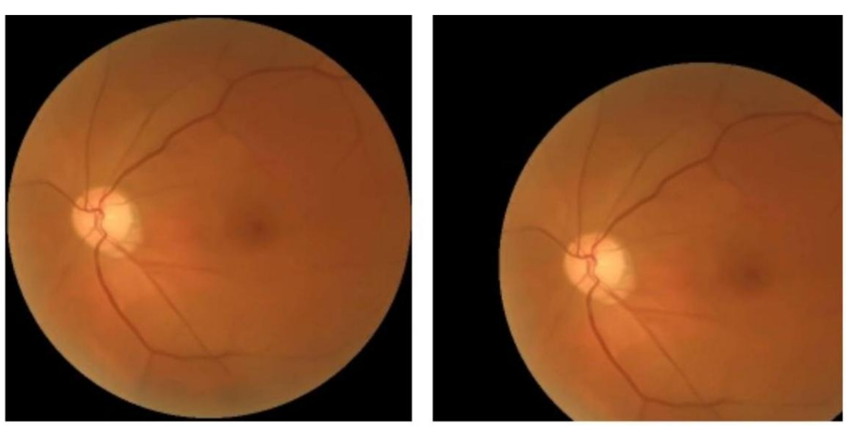

Fig .4 (a) Original fundus image, (b) translated fundus image.

5. **Brightness and Contrast Adjustment** This involves making direct changes to the optical values of the original image, aiming to simulate variations in shooting environments and conditions, such as lighting differences or

camera type. These techniques help the model learn more stable visual characteristics that are less affected by optical changes, thus enhancing its ability to generalize[29]. An example of the Brightness and Contrast technique is illustrated in Fig 2.5.

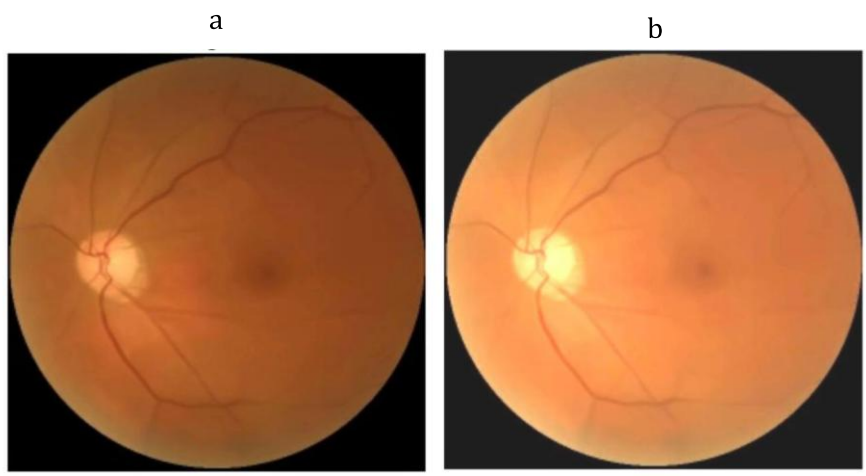

Fig .5 (a) Original fundus image, (b) Brightness and Contrast Adjustment fundus image.

6. **Noise injection** is the process of adding a matrix of randomly chosen values, usually sampled from a Gaussian distribution, to the original image. The purpose of adding noise is to replicate the natural noise that may occur during the image capture process, such as sensor noise or less-than-ideal shooting conditions. Noise injection enhances feature robustness during CNN training[23]. An example of noise and injection technique is illustrated in Figure 2.6.

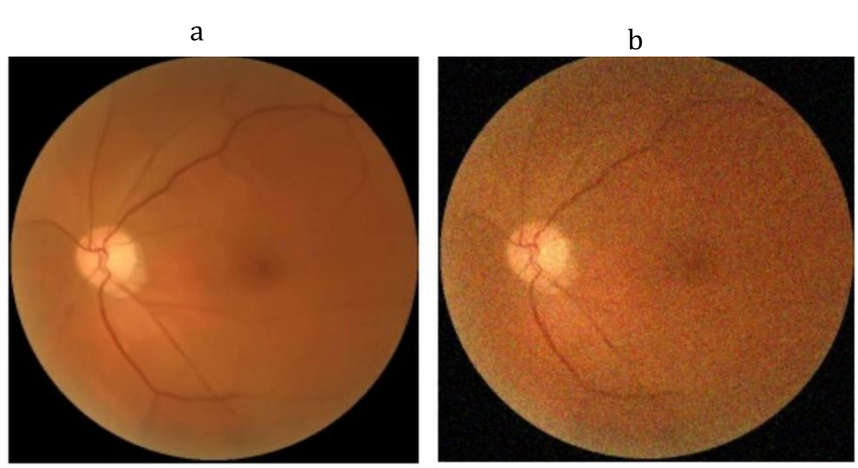

Fig .6 (a) Original fundus image, (b) fundus image with Gaussian noise.

3. Related Work

This section contains reviews of studies that employ traditional data augmentation methods including rotation, flipping, zooming, and enhancement of contrast with the aim of enhancing data quality and achieving class balance to classify cataract disease.

For example, Xie et al. [30] introduced the Cataract Severity and Diagnostic Image Dataset (CSDI), which is a fine-grained evaluation model that uses fundus image data for cataract severity assessment. The framework used the InternVL3-8B-hf model within the multimodal large language architecture (MLLM) architecture and was fine-tuned using LoRA technique for better cataract severity assessment. The CSDI dataset consisted of 187 fundus image cases along with their respective professional diagnosis and severity rating. Due to limited dataset size and potential class imbalance, the following data augmentation methods were used; that is, the image was randomly flipped, rotated between -15° and 15°, and zoomed at ratios of 1.05 to 1.17. The experiment results demonstrated competitive performance of the framework with accuracy and RMSE values of 59.46% and 1.12, respectively, outperforming several closed-source models.

In addition, Jabur et al. [31] developed a novel architecture for detecting senile cataract based on convolutional neural networks. The study used the Retina Dataset (2016), which is a subset of the Retina Blood Vessel Segmentation dataset and contains 300 healthy images and 100 cataract images, including a significant class imbalance. To overcome this problem, the researchers adopted a two-phase approach. First, the Retina Dataset was balanced by selecting 100 samples of each class. Then, traditional data augmentation techniques were performed using the KERAS library including random rotations between 0° and 40° and horizontal flipping, increasing the number of images from 400 to 1,000 (500 of each class). The framework employed a hybrid model that combines the ResNet-18 and SVM. According to the experimental results, the proposed framework achieved an accuracy of 87% and recall of 86%.

Moreover, Ismail W et al[32] introduced Cataract NetDetection, a deep learning-based classification framework applied to fundus images for cataract classification. The system relied on fused visual features extraction from paired left and right eye images to improve classification accuracy. The framework utilized several pre-trained architectures including DenseNet-121, ResNet-50, and Inception-V3 as feature extraction. The study employed the ODIR-5K dataset, containing approximately 5,000 fundus images covering eight ocular diseases. The dataset exhibited class imbalance (1,146 normal vs. 594 cataract cases). Therefore, the traditional augmentation techniques included rescaling, rotation, zooming, and horizontal flipping were applied to enhance sample diversity and reduce overfitting. The experimental results highlighted significant results in cataract classification with overall accuracy of 98% in certain experience.

Furthermore, Khan et al. [33]implemented an automated classification system for detecting cataracts based on the ResNet50 architecture that is specifically designed to retain high accuracy even in the case of incomplete retina images. The dataset consisted of 3,500 fundus images gathered from the HRF, IDRiD, ACHIKO-I, and ODIR image datasets and was divided into three categories, namely, normal, moderate, and severe cataracts. The dataset exhibited class imbalance since it had a larger number of images belonging to the severe category (500), as opposed to others (1,500). Four geometric augmentation techniques including rescaling, rotation, zooming, and flipping were used to prevent the model from overfitting, expanding the size of the dataset from 3500 to 17,500 images.

In another research, Andi Ibrahim et al. [34] presents novel AI-based solution for the early classification of cataracts by classifying fundus images into normal and cataract images. In this research article, the authors implement the EfficientNetB0 architecture within the convolutional neural network framework. The study utilized a relatively small Kaggle dataset consisting of 240 fundus images equally distributed between the two classes. Although the dataset was balanced, its limited size posed a challenge for deep learning training. Therefore, in order to address the problem of limited dataset availability, data augmentation techniques are used to reduce overfitting. The methodology used shows high efficiency, with training accuracy achieving 100% and testing accuracy achieving 95%.

In addition, Nguyen V et al[35] proposed an innovative hybrid technique, where DenseNet-121 is integrated with a technique known as "Image Quadration," where images of the fundus are divided into four parts to incorporate global and local features. The study combined two public datasets, producing a final dataset of 1,388 images used for binary classification of cataract and normal cases. Initially, the dataset exhibited considerable imbalance, containing 2,302 normal images and 694 cataract images. The researchers addressed this issue through random undersampling of the majority class and further applied image augmentation techniques, including image flipping, rotation, and zooming, to increase the amount of training data from 888 to 2,664 images. This hybrid technique resulted in an accuracy of 97.12%.

Moreover, Lahari P. L. et al.[36] proposed a novel framework known as Cataract States Detection Network (CSDNet), a lightweight deep learning model designed for cataract classification and identification of the four levels of severity. The model was specially designed for devices that have low memory storage capability. The study employed a preprocessed ODIR dataset containing 8,000 fundus images, binary and multi-class classification experiments are carried out. The dataset exhibited class imbalance, particularly in the Grade 2 cataract images. Which contained only 584 images. To overcome this limitation, traditional augmentation strategies, including image rotation, flipping, and shifting, were utilized to increase the number of images by 3 times from 2,000 images to 8,000 images. In particular, the CSDNet model experimental results demonstrated the effectiveness of the proposed framework, achieving accuracies of 97.24% and 98.17% for binary and cataract severity classifications, respectively.

Following the previous studies, Feng Z. et al. [37] proposed a novel hybrid deep learning-based cataract classification framework to enhance feature representation and classification performance. The proposed architecture integrates a Squeeze-and-Excitation (SE) module and a prototype network. The study utilized a dataset of 3,600 fundus images that was built by combining ODIR-5K dataset in a Kaggle competition, and retina dataset from GitHub. The resulting dataset was relative balanced, comprising 1,638 disease images and 1,962 normal images. However, controlled augmentation was done by rotating images with a transformation amplitude up to 0.2 and contrast adjustment to enrich the database without losing its clinical importance. The goal was to enrich the diversity of the data and simulate real scenarios while ensuring that the model learns the actual pathological features. As a result, the model obtained an accuracy of 98.75%. And area under the curve (AUC) of 0.9984.

In addition, He Xie et al.[38] proposed a DenseNet121- based framework to perform cataract classification and improving data diversity and reduce overfitting. The study utilized 8,395 images of fundus acquired from 5,245 individuals in three datasets ZEHWZ, ZEHHZ, and NEH. The developmental ZEHWZ dataset exhibited class imbalance as there are 2,141 non-cataract images, 1,918 mild cataract images, and 842 visually impaired cataract images. To address this issue, data augmentation was performed by applying cropping, rotation, horizontal, and vertical flips. Therefore, the training dataset was expanded sixfold from 4,901 images to 29,406 images. Thus, the accuracy for the detection of ocular cataract achieved 98.6%, and AUC became 0.999.

Furthermore, Yadav [39]aimed to design a cost-effective system for the early classification of cataracts and the classification of cases into four severity levels: normal, mild, moderate, and severe, the proposed framework combines deep learning techniques with a two-dimensional discrete Fourier transform (2D-DFT) applied to fundus images. The Fourier spectrum extracted from the 2D-DFT was computed and then used as an input representation for the deep learning model to facilitate feature extraction. The study compiled 1,835 fundus images from several public repositories including HRF, STARE, MESSIDOR, DRIVE, DRIONS_DB, and IDRiD, from which 1,600 high-quality images were retained. Unlike many previous studies, the dataset was intentionally balanced with 400 images per category. The researchers implemented traditional data augmentation techniques, which helped expand the training set and enhance sample variability. The proposed system achieved an overall accuracy of 93.10% in the four-class classification task.

Another study of Elloumi Y[40] proposed a highly complex stacking ensemble learning technique, incorporating Inception-V3, MobileNet-V2, and NasNet-Mobile architectures to evaluate the severity of cataracts. The utilized dataset consisted of 590 fundus images collected from the Cataract Dataset and ODIR repositories and categorized into healthy, mild, moderate, and severe stages. The dataset suffered from class imbalance, containing 220 non-cataract images compared with 65 mild, 145 moderate, and 160 severe cataract images. In order to reduce the problem of data imbalance, data augmentation techniques were employed, involving zooming, random corner shearing, shifting, and horizontal and vertical flipping. The proposed system achieved an overall accuracy of 93.97%.

A related study of Bina et al [41]performed a comparative evaluation of four CNN architectures "ResNet, MobileNet, GoogleNet, and the proposed Convolutional Neural Network" to classify four stages of cataract. The original dataset consisted of 339 images with imbalance in its category, which were expanded to 3200 samples through data augmentation techniques like random flip, rotation, zoom … etc. The result indicated the ResNet outperformed the other architecture with an accuracy of 93%, the proposed CNN architecture achieved of 92%, while MobileNet at 92%, and GoogLeNet at 86%.

Similarly, Imran et al. [42] performed a hybrid convolution recurrent neural network (CRNN) for the classification of cataract into four severity levels: normal, mild, moderate, and severe based on fundus images, transfer learning was employed using several architectures, GoogLeNet, AlexNet, ResNet and VGGN to extract multi-level feature representations and evaluate their classification performance. The study employed a large dataset of 8,030 high-resolution retinal fundus images collected from Tongren Hospital, China, with image dimensions of 3888 × 2592 pixels. The dataset was highly imbalanced, comprising 4,671 normal, 2,283 mild, 675 moderate, and 401 severe cases. To balance the dataset and avoid the problem of overfitting, the study utilized traditional data augmentation techniques to expand the dataset. The result indicated that the CRNN framework reached an accuracy of 97.39% in distinguishing among the four cataract classes.

Another study Junayed et al. [43] introduced a novel deep neural network called "CataractNet" for automatic cataract classification using fundus images. The architecture was carefully designed by tuning the loss and activation function and employing small convolution kernel with fewer parameters and layers. The study aggregated images from six public fundus repositories, producing an initial dataset of 1,130 images that was subsequently expanded to 4,746 images through augmentation. Due to limited dataset size and class imbalance, traditional augmentation methods including rescaling, 30° rotation, zooming, and horizontal flipping were employed to generate additional samples and improve training diversity. Following augmentation, the dataset contained 2,679 cataract and 2,067 non-cataract images. The experimental result demonstrated exceptional performance of the proposed model, achieving an accuracy of 99.31

In addition, Imran et al. [44] proposed a hybrid framework that integrates deep learning- based automatic feature extraction with the classification capability of support vector machines (SVM). The authors employed transfer learning using pretrained architectures, including (AlexNet, VGGNet, ResNet) to extract robust feature representation. The study utilized 8,030 high-resolution retinal images collected from Tongren Hospital and categorized into four severity levels. Similar to other clinical datasets, the class distribution was highly imbalanced, with severe cataract cases being substantially underrepresented. To further improve performance and minimize the risk of overfitting caused by imbalance dataset, traditional data augmentation techniques were applied during training. The experimental result confirmed the effectiveness of the proposed method, which attained an overall accuracy of 95.65%.

Although the previous research on the classification performance of the cataract detector reported encouraging results, most studies relied on traditional methods of data augmentation to increase the available training data. From the reviewed studies, the number of images used varied from 187 to over 8,000 fundus images with several datasets exhibiting significant class imbalance between normal and cataract classes or among different cataract severity grades. In terms of augmentation strategies, the most commonly adopted augmentation techniques included rotations, flips, crops, translations, adjusting the brightness of the image, and injecting noise into the images. Even though these approaches also enlarge the dataset of training images, they produce mostly distorted versions of the existing images with simple geometric or photometric transformations. Therefore, the resulting datasets may still lack sufficient variability of underlying visual patterns. Such limited diversity can restrict the learning capacity of deep learning models to capture strong feature representations which further can limit the capacity of deep learning models to generalize to unseen data. To summarize the reviewed studies in this section, Table 1 provides a comparative overview of the augmentation methods, Algorithms, and the classification result reported in the previous studies.

Table 1. Summary of the studies

No.	Study & year	Classification type	Dataset size	Augmentation method used	Algorithms used
1	Xie et al. 2026 [30]	Multi classification	1,000 images	Rotation, horizontal flipping	Support vector machine, ResNet-18
2	Jabur A et al. 2025 [31]	Binary classification	187 images	Cropping, horizontal flipping, rotation, zooming	InternVL3-8B-hf, Qwen2.5-VL-72B-Instruct, MiMo-VL-7B-SFT

3	Ismail W et al 2024 [32]	Binary classification	Normal 1,146 Cataract 594	translation, flipping, rotation, scaling, shading, cropping	Inception-V3, DenseNet-121, and RestNet
4	Khan et al 2024 [33]	Multi classification	3,500 images	zooming, flipping, rescaling, and rotation,	ResNet-50 (Processing Partial and Full images)
5	Andi Ibrm et al 2024 [34]	Binary classification	240 images	Not specified	EfficientNetB0 + AdaGrad Optimizer
6	Nguyen V et al 2024[35]	Binary classification	1,388 images	flipping, rotation, and zooming	Hybrid CNN (DenseNet121) + Majority Voting+ Image Quadration
7	Lahari P.L et al 2024 [36]	Binary and multi classifications	2,000 images	rotating, flipping, and shifting	Cataract States Detection Network based on CNN
8	Feng Z. 2024 [37]	Binary classification	3,500 images	rotating, scaling, clipping, flipping, and adding noise	prototype network +Squeeze-and-Excitation (SE) module + Restnet 50
9	He Xie et al 2024 [38]	Multi classification	4,901 images	rotation of 90°, cropping, and horizontal and vertical flipping	DenseNet121
10	Yadav S. 2023 [39]	Multi classification	1,600 images	rotation, flipping(horizontal), cropping, and	D-DFT → CNN (custom 6 conv layers + BN +

				shifting	clipped ReLU + max-pool + FC + dropout) → Softmax
11	Elloumi Y 2022 [40]	Multi classification	590 images	shifting, zooming, and horizontal and vertical flipping	Stacking Ensemble (NasNet-Mobile, MobileNet-V2, Inception-V3) with SVM
12	Bina R et al 2022[41]	Multi classification	1,600 images	random flip, rotation, zoom, and shift	GoogleNet, MobileNet, ResNet, and the proposed CNN model
13	Imran A. 2021 [42]	Multi classification	8,030 images	rotating, shifting, flipping and cropping	CRNN, AlexNet, GoogLeNet, ResNet andVGGN
14	Junayed et al. 2021 [43]	Binary classification	4,746 images	re-scaling, rotation, zooming, and horizontal flip,	CataractNet
15	Imran A.2020 [44]	Multi classification	8,030 images	rotating, cropping, flipping, and shifting	AlexNet + ResNet-18 + VGGNet-16+ SVM

4. Conclusion

This review focused on cataract classification using fundus images and highlights the significant role of traditional data augmentation techniques in developing effective deep learning models for cataract classification. The analysis reveals that traditional augmentation addresses two major challenges: limited dataset size and class imbalance. Nevertheless, despite their effectiveness, traditional augmentation techniques remain restricted to geometric and photometric transformations of existing images. They do not introduce a new pathological pattern. This limitation may affect the model generalization capability. Therefore, future research in cataract classification should explore modern data generation approaches or adopt hybrid strategies that combine traditional methods with advanced generation techniques. This integration could enhance dataset diversity and improve generalization performance.

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