IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 13, Issue 6, June 2024

DOI: 10.17148/IJARCCE.2024.13657

Survey Paper on Machine Learning Algorithms for Cataract Detection

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Abstract: Cataract is one of the foremost common eye maladies that cause visual impedance. Exact and opportune discovery of cataract is perfect way" the most perfect way to oversee the hazard and anticipate visual disability. As of late, cataract discovery frameworks based on counterfeit information have pulled in inquire about consideration. In this paper, we propose a novel profound neural framework, Cataract Net, for programmed discovery of cataract in fundus pictures. The misfortune and actuation capacities are tuned to plan the framework with less components, less preparing parameters and layers. Robotized conclusion of eye diseases using machine and profound learning models is getting to be increasingly common. Glaucoma, cataracts, diabetic retinopathy, astigmatism and age-related macular degeneration are common eye diseases that can cause genuine hurt. It is vital to capture eye contaminations early to maintain a strategic distance from genuine results. Early conclusion of eye maladies is fundamental for successful treatment.

Keywords: Cataract detection, eye disease, machine learning, glaucoma, deep learning.

I. INTRODUCTION

Cataract may be a clouding of the clear focal point of the human eye. Regularly, the lens centers light onto the retina. Once you have cataracts, this light is blocked from coming to the focal point, coming about in decreased vision.[1] It could be a common eye illness around the world that advances slowly and does not influence vision in its early stages.[2]

Cataracts are which the focal point of the eye gets to be cloudy. Side effects incorporate obscured, cloudy or twofold vision, affectability to light and trouble seeing at night. On the off chance that cleared out untreated, cataracts can lead to visual deficiency. There are distinctive sorts and causes of cataracts[2]. To begin with, the official portrayal of this eye condition is that cataracts are a condition in which the range around the canter of the eye gets to be cloudy due to a few variables counting (in arrange of significance): age, diabetes, inherent arrangement and eye injury.[3]

Machine learning, fake insights and profound learning calculations are innovative calculations that can offer assistance individuals with different eye illnesses through precise determination.[4] Early acknowledgment of eye illnesses and signs of eye infections is of most extreme significance to anticipate encourage eye issues and incapacities.

Eye diseases can lead to partial or complete vision loss if not properly examined early. Early diagnosis of eye diseases can prevent vision impairment.[4] Visual impairment, also known as vision loss, is usually defined by visual acuity [2]. Normal visual acuity is 20/20, but for people with visual impairment, it is lower than 20/40 or 20/60. The World Health Organization (WHO) estimates that at least 2.2 billion people will suffer from visual impairment or blindness in 2020, of which 1 billion will have moderate or severe visual impairment. could be prevented and treated.

Approximately 65.2 million people worldwide suffer from cataracts due to age-related degeneration. Factors that cause this disease, especially in the younger age groups, include a shortage of ophthalmologists, specialized medical facilities, and adequate medical equipment.[5] During surgery, ophthalmologists remove the cloudy lens from the eye and replace it with an artificial lens (called an intraocular lens or IOL).[3] The surgery takes about an hour and is painless**.** Comparing the results of these reports prove that there was only a slight improvement in the eye care system and controlling the vision loss during the last decade. Among the leading causes of blindness such as glaucoma [7], corneal opacity, trachoma, and diabetic retinopathy [8], cataract accounts for the most significant proportion.

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It is considered as one of the leading causes of blindness [5]. Cataract can be categorized into three main groups based on the location and area where it develops: Nuclear Cataract , Cortical Cataract [10], and Posterior Sub Capsular (PSC) Cataract . These three types of cataracts occur due to several common factors such as aging, diabetes, and smoking [5].

Machine learning, artificial intelligence, and deep learning algorithms have played a major role in shaping the 21st century. These technical algorithms have been shown to aid individuals with a variety of eye disorders via precise diagnosis. To prevent further difficulties and disruptions to the eyes, it is of the utmost importance to detect early signs of eye disorders or ophthalmic diseases.[8] When it comes to eye diseases, doctors typically rely on observational methods. However, this approach can be time-consuming and prone to human error, so it's crucial to incorporate machine learning and artificial intelligence algorithms thoroughly. This will ensure the safety of future complexions by providing appropriate clinical measures. Three subfields of artificial intelligence aim to mimic human behaviour and intellect: general, super, and narrow [1].

II. METHODOLOGY

This demonstrate is able to recognize cataract from fundus pictures.[4] The design of the proposed framework is appeared in Figure 1. The system of the cataract discovery framework incorporate In this segment, we depict the information collection handle and the devices utilized in information investigation, as well as the proposed profound learning strategy for cataract classification, particularly the multi-layer neural arrange design.[6] a few steps such as picture procurement, pre-processing, demonstrate usage, and execution examination. These steps are clarified in more detail within the taking after segments.

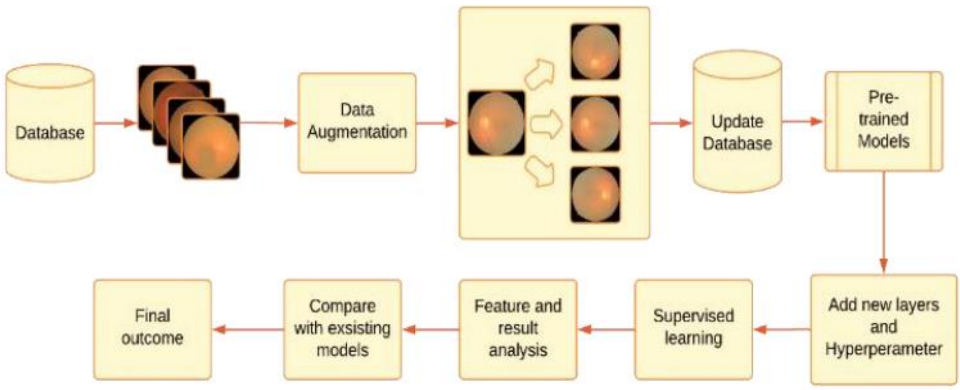

Fig1. Workflow of eye cataract detection

A.Dataset properties:

In this study, we used data from publicly available datasets, namely Eye Disease Recognition and Eye Disease Classification, as well as data from Kaggle datasets. The figure shows a visual representation of the dataset and examples of fundus images included in the study. [8]The above dataset contains images of normal and cataract eye diseases that have been labelled by qualified experts.

The combined dataset used in this study contained two classes, cataract and normal, with a total of 2000 images. The cataract class contained 1000 images and the normal class contained 1000 images that were properly labelled and split in the right ratio.[6] To increase the amount of data in the dataset, image augmentation was applied. After augmentation, the total number of images in the dataset was increased to 5000. 80% of the data was used during the training phase and the remaining 20% was reserved for the testing session.[3] The combination of datasets and augmentation techniques used in this study resulted in a diverse and extensive dataset that was used to develop and evaluate an automated system for detecting cataracts in eye images.

B. Data Pre-Processing

Multiple fundus image datasets were acquired and a pre-processing pipeline was implemented to ensure consistency and improve data quality.[5] Images were selectively filtered to include only cataract and normal images and exclude other images such as diabetic retinopathy, hypertension, pathological myopia, glaucoma, and age-related macular degeneration among others.

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To standardize the image sizes, the OpenCV library was utilized for resizing and normalization, involving subtracting the mean value from all pixels.[7] Each image was appropriately labelled as either cataract or normal, and the dataset was then converted into an array format using NumPy, facilitating the subsequent training process. To enhance the model's capacity to generalize to new images, augmentation techniques were applied, including rotation and flipping. These techniques were implemented using the Keas framework . The random augmentation process was applied to both the training and testing data to enhance the model's ability to learn with a larger dataset.[8]

C. Model Selection

In order to detect cataracts in fundus eye images obtained from ocular datasets, various model architectures were employed, namely VGG19, NASNet, ResNet50, and MobileNetV2. These architectures were selected to enhance the accuracy of cataract detection and improve the overall performance of the models.[6] A detailed analysis of the method architecture is presented below for a better understanding.

1) Visual geometry group architecture: The Visual Geometry Group at the University of Oxford developed a CNN model called VGG19, known for its depth and use of small convolutional filters and max pooling layers [39]. In VGG19, feature maps are down-sampled by small 3x3 convolutional filters that focus on the most important features.[3] To enhance the overall effectiveness of the model and address overfit ting, we implemented several techniques, such as adding a dense layer with 512 neurons and a ReLU activation function, a dropout layer with a rate of 0.5, and a dense layer with 49 neurons and a sigmoid activation function.[6]

2) Neural architecture search: Neural Architecture Search (NAS) is a type of convolutional neural network developed by the Google Brain team . The goal is to design architecture with minimal human intervention and limited resources. In our study, we used a pre-trained NASNet model with Image Net weights and added some additional layers.[10] We introduced fully connected layer architecture of 512 neurons with ReLU activation, followed by dropout with a rate of 0.5. Next, we added another fully connected layer of 49 neurons with sigmoid activation.

D. Evaluation Metrics

This subsection elucidates the confusion metrics employed to gauge the efficiency of the models. The matrix provides insight into the number of true positives, true negatives, false positives, and false negatives, allowing for a more in-depth analysis of the model's strengths and weaknesses.[7] Confusion matrix is widely used in various fields, such as medical diagnosis, fraud detection, and image classification, where the accuracy of the predictions is critical. By analysing the confusion matrix, data scientists can identify the areas where the model is performing well and areas where it needs improvement, enabling them to fine-tune the model to achieve better results.[8]

III. EXPERIMENTAL EVALUTION

In this section, we describe the experimental setup, metrics, a comparative analysis with various existing methods, discuss limitations and challenges, and draw conclusions for the proposed work.

1. Dataset

First, we compiled a dataset called ODIR version 7, which contains 4166 JPG images of eyes. The dataset contains 1,293 cataract images and 2,873 normal eye images. We used the Glaucoma dataset version 1, which contains 4,854 JPG images of glaucoma and normal eyes. For DR (Diabetic Retinopathy), we compiled the Diabetic Retinopathy dataset version 1, which contains 13.3k JPEG images of eyes. These three datasets were combined to train models for cataract, glaucoma, DR, and normal eyes.[6] Some of the training examples of the datasets are shown in Figure 2. The details of the datasets are listed in Table 1. A diagram of the datasets is shown in Fig4. Split the entire dataset.

The split ratio of approximately 83% for training and 17% for testing represents a balanced ratio of 5:1, which ensures a rich training set to facilitate the model learning process while retaining a significant portion of the training set.

The data is reserved for testing and evaluation purposes.[2] We then cross-validated the proposed model using Kaggle datasets of cataract, glaucoma detection, and diabetic retinopathy (reduced version). The cataract dataset contains 602 PNG images of cataract and normal eyes. The glaucoma dataset consists of 2005 JPEG images of glaucoma and normal eyes, while the DR Dataset contains 70.2K JPEG images of DR and normal eyes.[5]

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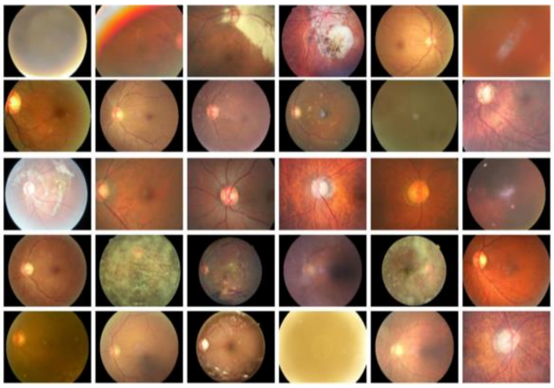

Fig2. Training Samples

Class Label	Training Data Samples	Testing Data Samples
Cataract	1500	400
Glaucoma	1200	200
DR	1200	200
Neutral	1000	150
Total	4900	950

Table1. Dataset Details for Training and Testing

2. *Results and analysis*

For the performance evaluation of the proposed model, we have utilized various metrics such as Precision, Recall, and Accuracy. Moreover, these metrics are relied on true positive (TP), false positive (FP), true negative (TN), and false negative (FN). [1]The TP refers to the correctly classified diseases by our proposed model, FP refers to the number of images that

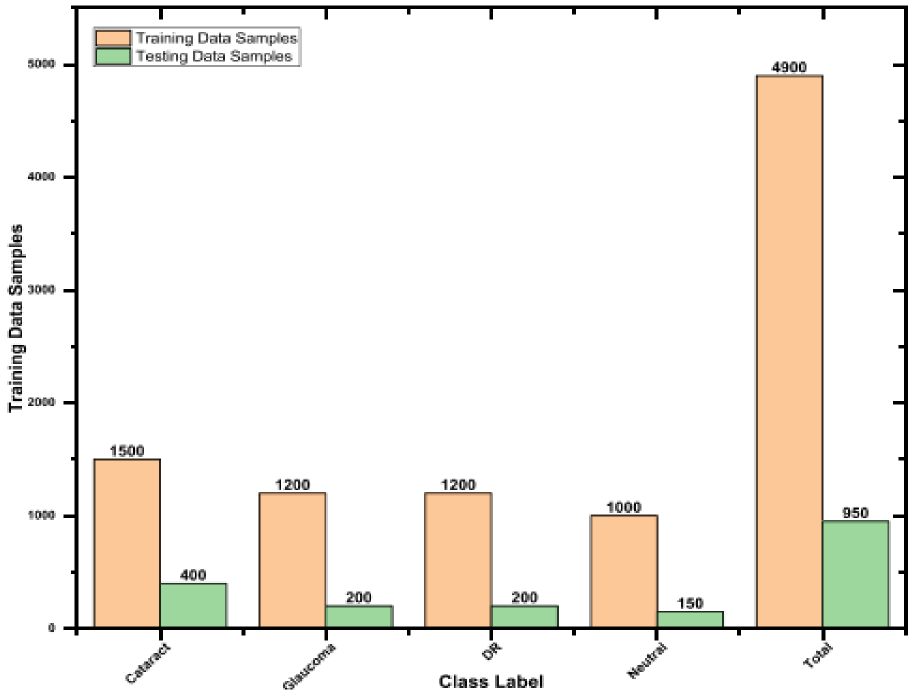

Fig4. Plot for Training Dataset

Were incorrectly classified as another disease than the actual one, and FN denotes the number of diseases that were incorrectly classified as negative i.e., neutral class, and TN refers the number of images that were correctly classified as a negative class such as neutral. Furthermore, precision refers to the fraction of TP over the total images classified as positive. The mathematical equation is given below.

Precision = TP/TP+FP

The accuracy of the system indicates the correctly classified images by the proposed system. The equation is presented below.

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Accuracy = TP+TN/TP+TN+FP+FN

The recall is the fraction of the classified positive class images to all images of positive class whether they were classified as a negative class by the system.[4] The recall value closer to 1 refers to the better model. The equation of Recall is given below.

Recall = TP/ TP + FN

IV. LIMITATIONS

1. Reduced Visual Acuity: Conditions like cataracts, macular degeneration, and diabetic retinopathy can significantly reduce sharpness of vision, making it difficult to read, drive, or recognize faces.

2. Night Blindness: Conditions like retinitis pigments can impair vision in low light conditions, making it challenging to navigate at night or in dimly lit environments.[5]

3. Difficulty with Daily Activities: Tasks such as cooking, cleaning, personal grooming, and shopping can become challenging, affecting self-sufficiency.

4. Social Interaction: Difficulty recognizing faces and reading social cues can impair social interactions and relationships.[3]

5. Educational and Employment Challenges: Children and adults with vision impairments may face obstacles in educational settings and workplaces, requiring special accommodations and adaptive technologies.[2]

6. Lack of Cure: Many eye diseases, such as glaucoma and macular degeneration, currently have no cure and can only be managed to slow progression.

7. Access to Treatment: Availability and affordability of treatments like surgeries[8], medications, or specialized eyewear can be limiting factors for many individuals.

8. Side Effects: Treatments for eye diseases, including medications and surgeries, can have side effects or complications that impact overall health and well-being.[7]

V. CHALLENGES

➢ **Medical and Technical Challenges**

1. Early Detection:

○ Subtle Symptoms**:** Early-stage cataracts often cause mild vision changes that can be mistaken for normal aging or other eye conditions[9], making early detection difficult.

○ Advanced Imaging Requirements**:** Advanced imaging technologies like slit-lamp bio microscopy or optical coherence tomography (OCT) are often required, which may not be accessible in all healthcare settings.

2..Diagnostic Equipment:

○ Cost and Accessibility: High-quality diagnostic equipment is expensive and may not be available in low-resource settings.

○ Training: Proper use of diagnostic tools requires [9] specialized training, which may be lacking in underdeveloped areas.

○

➢ **Patient-Related Challenges**

1. Awareness and Education:

○ Lack of Awareness: Many patients are unaware of the symptoms of cataracts and may not seek medical attention until significant vision loss occurs.

○ Misconceptions: Cultural or personal misconceptions about cataracts and eye care can prevent individuals from seeking timely diagnosis and treatment.[6]

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2. Access to Care:

- Geographical Barriers: In rural or remote areas, access to eye care professionals and diagnostic services is often limited.
- Economic Barriers: The cost of eye exams and diagnostic tests can be prohibitive[4] for individuals without adequate insurance or financial resources.

➢ **Operational Challenges**

1. **Screening Programs**:

- Implementation: Establishing effective and widespread screening programs can be logistically challenging, particularly in low-income regions.
- Follow-Up: Ensuring patients follow up with necessary diagnostic tests and treatment after initial screening is critical but often difficult to manage.[1]

2. **Data and Record Keeping**:

- Consistency: Maintaining consistent and comprehensive patient records is crucial for tracking disease progression and outcomes but is often hampered by[10] poor record-keeping practices.
- Integration: Integrating data from various sources (e.g., primary care, ophthalmologists, imaging centres) can be technically challenging.

➢ **Technological Advancements and Innovations**

1. **Development of AI and Machine Learning**:

- Accuracy: Developing AI algorithms that can accurately detect cataracts from imaging data requires large datasets and extensive validation.[9]
- Bias and Generalizability: Ensuring AI models are unbiased and generalizable across diverse populations is a significant challenge.

2. **Portable and Affordable Devices**:

- Innovation: Creating portable, affordable, and easy-to-use diagnostic devices that can be used in remote or low-resource settings is a technological [7]challenge.
- Distribution: Ensuring these devices reach the areas most in need involves overcoming logistical and economic hurdles.

VI. CONCLUSION

The current slant towards large-scale organized learning calculations in counterfeit insights requires adequate and huge datasets to consequently extricate important highlights and classify illnesses.[6] This article has two targets. To begin with, to work with a expansive picture dataset for the investigate community working on atomic cataract discovery utilizing computational calculations. Diverse profound convolutional neural organize designs have been compared with exchange[8] learning to attain precise classification of fundus pictures for cataract determination. The proposed procedure can too be utilized for location and classification of other diseases, e.g., B. Knee Malady. Within the future, we would like to improve the proposed strategy by utilizing programmed fine-tuning procedures to play down the preparing time.[7] Patients may have other maladies that influence the cataract highlights in opening light pictures. These infections cannot be recognized from cataract. Hence, encourage inquire about ought to centre on moving forward the strategy.[4] Due to the high-level highlights extricated for cataract classification, the proposed CNN empowers programmed preparatory conclusion of atomic cataract in opening lamp images. [9]At long last, it can be concluded that the calculation is valuable in performing the primary inquire about step for a rectify therapeutic determination.

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