RESEARCH ARTICLE

Enhancing Ocular Health Precision: Cataract Detection Using Fundus Images and ResNet-50

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Abstract

Cataracts are a leading cause of blindness in Pakistan, contributing to more than 54% of cases due to poor living condition, nutritional deficiencies, and limited healthcare access. Early detection is critical to avoid invasive treatments,but current diagnostic approaches often identify cataracts at advanced stages. This paper presents an advanced,automated cataract detection system using deep learning specifically the ResNet-50 architecture, to address this gap. The model processes fundus retinal images curated from diverse datasets, classified by ophthalmologic experts through a rigorous three-stage process. By leveraging the ResNet-50 model, cataracts are categorized into normal,moderate,and severe, achieving an accuracy of 97.56% on full images. Notably, the system performs well even on partial images with 70% visibility, maintaining an accuracy of 95.23%, thus minimizing the need for extensive images restoration. The dataset was augmented to include 17,500 images,ensuring robust training. The model's ability to detect cataracts with high precision in images with varying visibility(70% ,80%,85% and beyond) demonstrate its flexibility and reliability, consistently achieving accuracy above 95.50%. This research offers a non-invasive, efficient solution particularly suited for remote areas, addressing the limitations of the late-stage diagnoses. It represent a significant advancement in cataract detection and has the potential to revolutionize global cataracts identification through early, accurate intervention.

Keywords: cataract detection, deep learning, ResNet-50, eye fundus images, health care, partial image.

1 Introduction

Cataracts are a worldwide prevalent eye disease, characterized by gradual clouding of the lens with

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time, which restricts the clear passage of light rays [1, 2]. This condition, which affects people worldwide, manifests itself in varying degrees, from minimal vision impact to severe obscuration, reducing the visual field to an interplay of light and darkness [3]. Symptoms become apparent when the haziness reaches a point of severe vision impairment, often accompanied by compromised vision, especially in glare and in nighttime conditions. Additional indicators include frequent changes in eyeglass prescriptions, reduction in color intensity, image yellowing, in rare instances, occurrences of double vision. Cataracts significantly contribute to global visual impairment, accounting for 33% and constituting a substantial 51% of global blindness [4, 5]. In Pakistan, over 9 million individuals grapple with varying degrees of vision impairment, with more than 80% of the population residing in rural areas [6]. The demanding workload of ophthalmologists and physician [7], primarily focused on routine eye examinations, leaves little time for critical surgeries that could prevent blindness.

Although competent ophthalmologists have the experience to eliminate cataract-induced blindness through surgical interventions, the current cadre faces challenges in meeting the required volume of surgeries [8]. Moreover, Figure 1. Showing different types of eye cataracts. Several barriers impede efforts to prevent blindness on a larger scale, including a lack of public awareness regarding eye health, physical accessibility to medical facilities, financial burdens associated with medical care, and instances of unsuccessful surgical procedures [9]. Cataracts are mainly classified into three types: Nuclear Sclerotic Cataracts (NS), Cortical Cataracts (CS), and Posterior Subcapsular Cataracts (PSC) [10]. Prompt diagnosis and treatment of cataracts can greatly lower the risk of blindness and minimize the discomfort that may arise from surgery [11]. The prevention of cataracts hinges on early detection, and recent explorations in automatic cataract detection have delved into various imaging techniques. Fundus images, particularly those captured with a fundus camera, have received significant attention due to their user-friendly nature, offering a viable option for healthcare professionals and patients [12]. The literature has examined machine learning-based automated cataract detection methods in great depth. However, these systems often face challenges such as suboptimal detection accuracy and high computational costs [13]. Meanwhile, deep learning systems have demonstrated remarkable results in autonomously detecting age-related eye conditions [14, 15]. In order to overcome the limitations of existing approaches, this research provides an enhanced system for automated cataract identification and classification utilizing fundus images. The proposed approach categorizes patients into three groups: normal, moderate, and severe cataract conditions. As part of this research, a deep neural network model for cataract detection based on fundus images is developed, an algorithm for disease detection and classification is developed, and the system is enhanced to operate effectively with partial images (up to 70%).

1.1 The rest of the paper is organized as follows

Related Work section II: defines the already available techniques for cataract detection. **Methodology section III:** This section describes the research design, detailing the data collection methods and techniques utilized in the study. **Results and Discussion section IV:** Presents the results of the study and discusses their implications. It showcases the accuracy achieved by the ResNet-50 model on full fundus images and partial images, emphasizing the efficiency and effectiveness of the proposed system. **Comparative Analysis section V:** The results obtained from the proposed system are compared with various other models. Provides a comparative evaluation that demonstrates the superiority or advantages of the ResNet-50-based approach in terms of accuracy, efficiency, and practical applicability. **Conclusion and Future Work section VI:** serves as the conclusion of the paper.

1.2 Motivation

The potential to revolutionize cataract detection and management is particularly critical in regions such as Pakistan, where the burden of blindness due to cataracts is alarmingly high [16]. According to Vision 2020, there were approximately 285 million blind and visually impaired individuals worldwide in 2011 [17]. Cataracts account for more than half of all visually impaired people, affecting nearly one-third of the global population. This condition, along with uncorrected refractive errors, stands as the leading cause of vision impairment [18]. Based on estimations from the World Health Organisation (WHO), approximately one billion of the 2.2 billion persons who suffer from visual impairments globally can be averted [19]. By 2025, cataracts alone are projected to cause blindness in around 40 million people. This research aims to address this pressing public health issue by developing advanced, accurate,

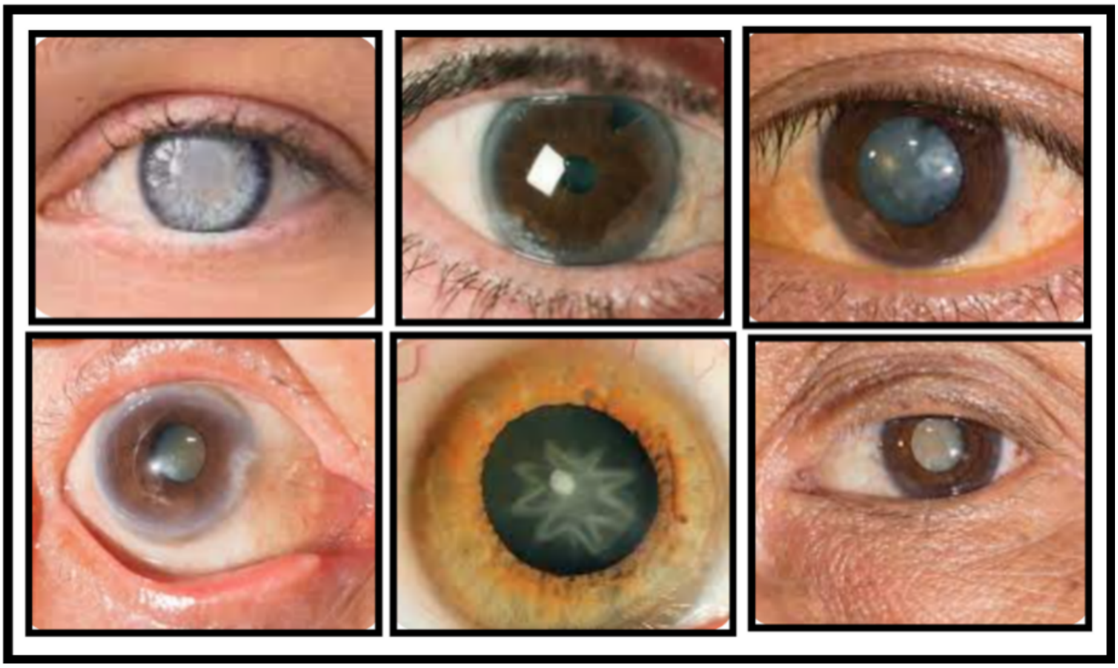


Figure 1. The sample image showcases a variety of eyes from different age groups, all displaying different stages of cataract disease. Cataracts, which can cause the lens of the eye to become cloudy, are evident in each sample, demonstrating the progression and severity of the condition. If not addressed, cataracts have the potential to result in blindness.

and cost-effective solutions for cataract detection, thereby improving early diagnosis and management, particularly in underserved regions [20].

1.3 Contribution of the study

- The study presents a sophisticated automated cataract detection system using ResNet-50, achieving high accuracy in cataract classification, with 97.56% accuracy on full fundus images and 95.23% on partial images with at least 70% visibility.
- The research shows the model's ability to accurately detect cataracts in images with only 70% visibility, highlighting its robustness and practicality in real-world situations where complete images may be unavailable.
- In the best of our knowledge for the first time working on cataracts images with only 70% visibility.
- Provides a non-invasive, scalable solution for early cataract detection, benefiting remote and underserved populations and addressing the global cataract burden.

2 Related Work

Several methodologies have contributed significantly to the advancement of the domain of cataract detection and classification, employing machine learning and deep learning methods. These approaches collectively improve the automation and precision of cataract diagnosis, providing essential tools for healthcare professionals and potentially optimizing government assistance programs for poor communities.

In machine learning-based methods for eye cataracts, Akram et al. [21] automated cataract grading, achieving reliable results by comparing grades from different grading methods and got the accuracy of 94%. However the methods not got better accuracy.

Yang et al. [22] demonstrated superior grading performance using multi-feature and stacking methods and accuracy of six-level grading achieved by the their method is up to 92.66% on average, the highest of which reaches 93.33%. The proposed method achieves 94.75% accuracy on four-level grading for cataract.

Song et al. [23] employed gray-level with grey gradients co-occurrence vectors and achieved a four-stage cataract classification accuracy of about 88.60%. Unfortunately they have to combine several weak binary classifiers into a strong multicategory classifier, though it may have better performance, but the procedure is very time-consuming.

Jagadale et al. [24] employed the Hough circle detection transform and SVM for cataract diagnosis with 90.25% accuracy. However in healthcare domain we need a very high accuracy.

Cao et al. [25] suggested a method for displaying texture information using Haar wavelet features, achieving increased cataract detection and grading accuracy. The accuracy's of the two-class classification (cataract and non-cataract) and four-class classification are 94.83% and 85.98%, accuracy respectively.

Harini et al. [26] presented automatic cataract classification using wavelet, spatial domain, SVM, and RBFN classifiers that it shows 90% sensitivity and 93.33% specificity. However the model need improvement to identify eyes disorders.

Askarian et al. [27] utilized luminance-based image analysis with SVM to categorize cataracts with 96.6% accuracy. unfortunately their model did not show the age of the disease. Which is important in medical domain.

Hossain et al. [28] employed DCNN and ResNet for automatic cataract detection with a test set accuracy of 95.77%. However their model is unable to detect the partial or mild cataract in retinal fundus images.

Rana et al. [29] created a sequential classifier that achieved a 90% accuracy rate in cataract detection.However their research used a very limited dataset of 50 peoples total.

Guo et al. [30] proposed a wavelet transformation strategy for categorization and classification of cataracts with 90.9% and 77.1%, respectively. Yang et al. [31] investigated cataract detection and classification techniques,their ensemble classifier is 93.2% and 84.5% in terms of the correct classification rates for cataract detection and grading tasks, respectively. Pratap et al. [32] utilized CNN pre-trained models for transfer learning with accuracy 92.91%. Xiong et al. [33] presented a multi-feature collection approach for automatic cataract classification with an accuracy of 94.75%. However the above articles accuracy is less then 95% in medical domain we need high accuracy.

These paper demonstrate significant advancements in machine learning and deep learning approaches, as well as the variety of approaches and techniques used to improve cataract identification and grading.

3 Dataset

To improve deep learning-based classification, a robust data set is essential. In this study, Cataract act retinal fundus images were sourced from diverse datasets, including the high-resolution fundus (HRF), Indian diabetic retinopathy images dataset (IDRiD) [34], ACHIKO-I fundus image dataset [35], ocular disease intelligent recognition (ODIR) [36], and vessel extraction database (DRIVE) [37]. The data set comprised images classified into three categories: normal, moderate, and severe Cataracts. The classification phase encompassed a total of 3,500 images, with 40% (1,400) for training, 40% (1,400) for validation, and 20% (700) for testing. Refer to Table 1 and Figure 2 for a detailed description and division of the data set.

Table 1. Dataset Description.

S.No	Class	Full/Half Images	Color	Total
1	Normal	500/300	RGB	800
2	Moderate	1500/750	RGB	2250
3	Severe	1500/750	RGB	2250
Total		3500/1800		5300

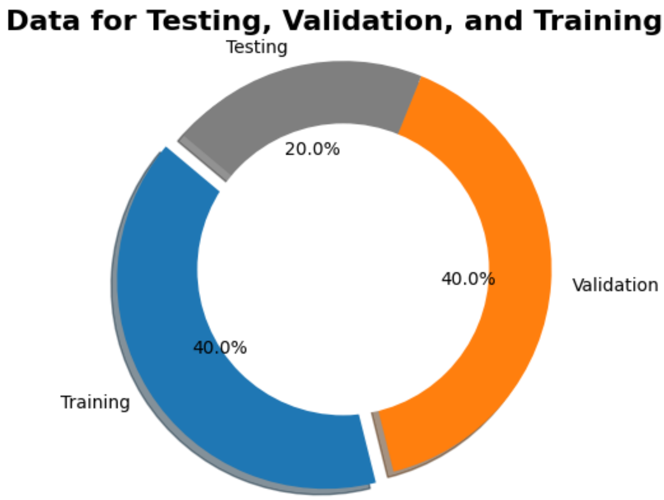


Figure 2. The chart illustrates the division of a dataset into three parts: 40% for training, 40% for validation, and 20% for testing. Training data is used to develop the model, validation data is used to tune it, and testing data evaluates its performance.

4 PRE-PROCESSING

Images from various sources were standardized to a uniform format of 100x100x3 pixels for RGB images. In order to facilitate comparable pixel distributions across the three channels, the intensity was normalized across the channels. Figure 3. Shown Cataract and Non-Cataract Partial Images. Image normalization was a crucial step before training to ensure efficient convergence, as shown in Table 2.

Table 2. Dataset Analysis.

Class Name	Total images	Size	Color
Normal images	1500	100×100	RGB
Moderate images	1500	100×100	RGB
Severe Images	500	100×100	RGB

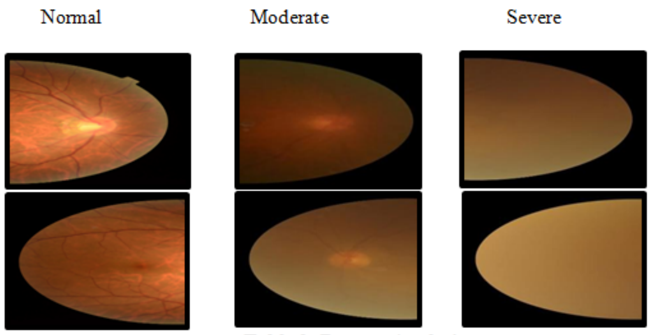


Figure 3. The image presents partial views of eyes categorized into three stages: normal, moderate, and severe cataracts. The normal category shows clear retinal images, while the moderate and severe categories depict increasing cloudiness and opacity due to cataract progression.

4.1 DATA AUGMENTATION

To address the challenge of limited training data, data augmentation was applied using four geometric transformations: rescaling, rotation, zooming, and horizontal flipping. This increased training samples, resulting in an additional 1,400 images and preventing overfitting. The image of the dataset, shown in Table 3, was displayed after data augmentation was applied. The overall Cataract image count, with and without transformation, was 17,500 and 3,500, respectively.

4.2 Details of Partial Images

A subset of partial images was created from the complete image dataset, where 30% of the image view was blurred or covered with eyelids, and 70% of the image was visible. Refer to Figure 4 for details of the partial images: this simulated scenario in which certain visual features were unclear, mimicking real-world diagnostic challenges. The machine was trained to reject images with less visibility than 70%, mimicking the doctor's decision-making process.

5 ResNet-50

ResNet-50 is a convolutional neural network consisting of 50 layers, designed to learn residual mappings rather than direct feature mappings [38, 39]. This architecture addresses the issue of vanishing or exploding gradients by incorporating the concept of residual learning within the Residual Network framework. Instead of directly approximating the underlying mapping $H(x)$, ResNet-50 learns a residual function $F(x) = H(x) - x$.

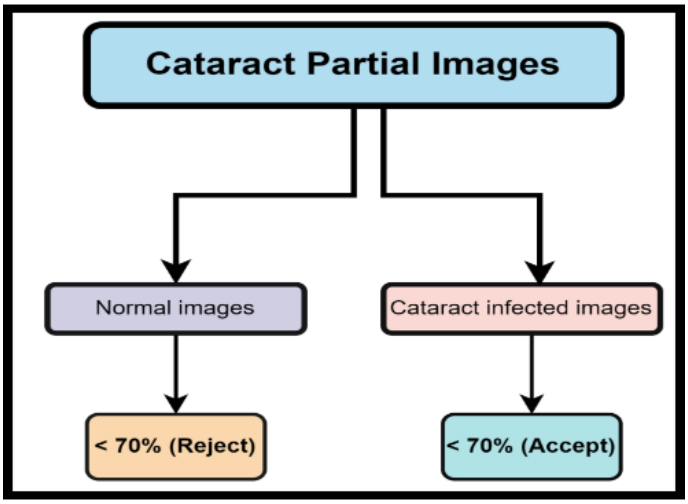


Figure 4. The diagram illustrates the classification process for partial images in a cataract detection dataset. Normal images with less than 70% visibility are rejected, while cataract-infected images with less than 70% visibility are accepted for further experiments on partial images.

5.1 Residual Learning

In traditional neural networks, each layer is expected to directly approximate the desired underlying mapping $H(x)$. However, in ResNet-50, the network learns the residual function $F(x)$, and the output of a stack of layers is expressed as:

$$y = F(x) + x \tag{1}$$

where $F(x)$ is the learned residual and x is the input.

Therefore, if our desired underlying mapping is $H(x)$, then we have:

$$F(x) = H(x) - x \tag{2}$$

Thus, the output becomes:

$$y = F(x) + x = H(x) - x + x = H(x) \tag{3}$$

This approach simplifies the learning process by making it easier to learn identity mappings.

5.2 Architecture

ResNet-50 comprises 50 layers, including convolutional, batch normalization, and identity mapping layers. The network can be divided into several stages, each consisting of multiple residual blocks.

Table 3. Data Augmentation Images Comparison.

Category Name	Dataset (original)	Dataset (after transformation)	Percentage
Normal images	1500	7500	42%
Moderate images	1500	7500	42%
Severe images	500	7500	16%
Total	3500	17500	100%

5.3 Mathematical Formulation

A residual block can be mathematically formulated as follows:

- Let x be the input to the residual block.
- The block applies a series of convolutional, batch normalization, and activation layers to compute $F(x)$.
- The output of the block is:

$$y = F(x) + x \tag{4}$$

The residual block addresses the vanishing/exploding gradient problem by ensuring that the gradient may pass through the network more easily.

5.4 CNNś Deeper Architecture Difficulties

CNN's deeper architecture faces difficult training, vanishing gradient, and degradation difficulties because it can extract a lot of features [40, 41]. To address challenges such as hard training, vanishing gradients, and degradation faced by CNN's deeper architecture, our proposed methodology leverages a ResNet-50 architecture, as shown in Figure 5. Illustrates the different layers of the ResNet-50. This design introduces the concept of fast connections, which allows the direct transmission of data leading to deeper layers, mitigating the problem of vanishing gradients. A bottleneck design is used as the building block of ResNet-50, which reduces the number of mathematical operations and parameters, resulting in faster training for each layer. ResNet-50 has three layers as opposed to two, with a residual block acting as the network's primary building block. In this block, convolution layers with an equal number of filters and a modest filter size are used to combine the input from the first layer with the output from the second layer. . We add 64 more kernels with a 2-sized step to convolution on a 77-kernel matrix, and then we add a layer of max-pooling with a 2-stride size. Three times each, there are nine layers, including 3x3 and 64 kernels per kernel, one layer featuring 1x1 and 64 kernels, and one layer featuring 1x1 and 256 kernels. The system consists of twelve layers that have four iterations of 1×1, 128, 3×3, and 1×1, 512 kernels. There are 18 iterations in each layer: 2×3 256, 1×1 with 1024 cores, and 1×1, 256 cores. The final nine layers are each iterated three times, resulting in 50 layers in total. Based on the Softmax activation function, a 1000-node fully connected layer is constructed. ResNet-18, ResNet-34, and ResNet-50 are among the various versions of the ResNet architecture. In pre-trained convolutional neural networks, the first fully connected layer is often replaced with a Global Average Pooling (GAP) layer. By utilizing the last convolution layer's output feature map, the GAP layer minimizes training data and overfitting in CNN models.

In our proposed work, the Cataract classification is performed after feature extraction using all three pre-trained convolutional neural network models. The key mathematical concepts in CNNs, including convolution and the convolution operation, are applied in the feature extraction process. The entire process is visualized in the block diagram presented in Figure 6. This methodology ensures efficient feature extraction and classification for accurate Cataract diagnosis.

5.5 Performance Evaluation Criteria

Beyond accuracy alone, a thorough review is necessary to determine the model's efficiency; in this study, evaluation criteria were recall/sensitivity, accuracy, specificity, and the F1 score. Confusion matrices are necessary for comparing variables and assessing model performance. They comprise true negatives (TN), false negatives (FN), true positives (TP), and false positives (FP), as shown in Figure 10.

5.6 Accuracy

A model's accuracy is measured by the proportion of true finds (true positives and true negatives) in all cases that are examined.

Mathematical Formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

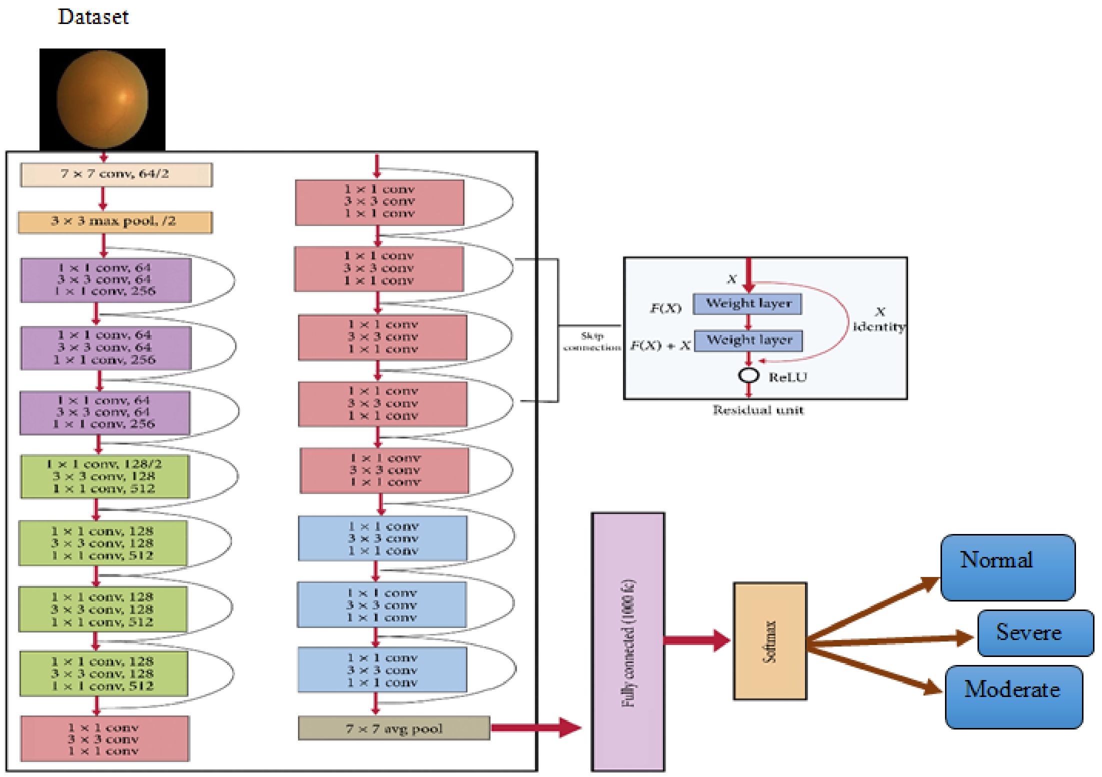


Figure 5. Take dataset is input, shown as an eye image. The initial layers are convolutional, starting with a 7x7 conv layer (64 filters, stride 2), followed by a 3x3 max pooling layer (stride 2), then 1x1 conv (64 filters), 3x3 conv (64 filters), and 1x1 conv (256 filters). This is followed by residual blocks with layers like 1x1 conv (128 filters), 3x3 conv (128 filters), and 1x1 conv (512 filters), featuring skip connections. Each residual block processes the input (X), applies convolutional layers (F(X)), and adds the input back to the output (X + F(X)). After convolutional and residual layers, the data flows through a fully connected layer with 1000 neurons, then a SoftMax layer for classification into Normal, Moderate, and Severe classes. The different colors represent various layers and parameters, with arrows indicating the data flow through the network.

5.7 Precision

Precision is the proportion of correctly recognized true positives among all instances projected to be positive. It is also known as positive predictive value.

Mathematical Formula:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

5.8 Recall

The model's recall measures how well it can accurately identify true positives out of all real positive cases.

Mathematical Formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

5.9 F1-Score

The F1 score offers a single measure that strikes a compromise between recall and accuracy, calculated as a harmonic mean.

Mathematical Formula:

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

5.10 Rectified Linear Unit (ReLU)

In neural networks, the Rectified Linear Unit (ReLU) is an activation function that adds nonlinearity. It outputs the input directly if it is positive and zero otherwise. This helps solve the vanishing gradient problem.

Mathematical Formula:

$$\text{ReLU}(x) = \max(0, x) \tag{9}$$

5.11 Softmax

In classification models, Softmax is commonly used in the output layer as an activation function. After logitizing the raw scores and normalizing by the total of all exponentiated logits, the logits are turned into probabilities. This ensures that the output values are

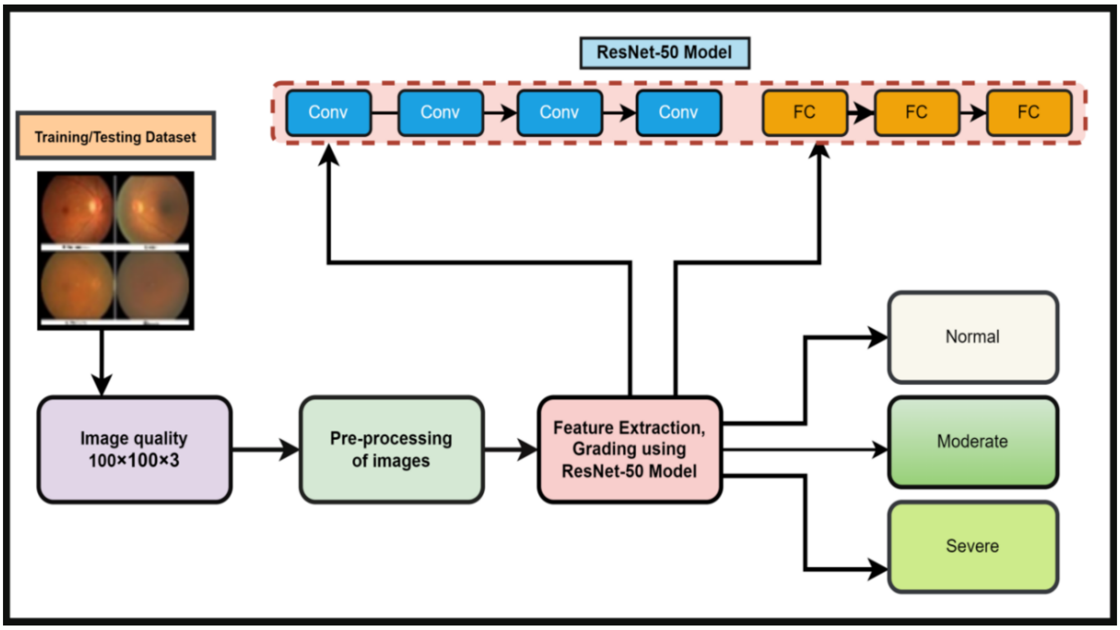


Figure 6. Illustrates the process of using a deep learning model for retinal image classification. The training/testing dataset consists of retinal images resized to 100x100 pixels with three color channels. These images undergo pre-processing steps to enhance their quality through normalization and augmentation. The pre-processed images are then fed into a ResNet-50 model, a deep residual network with 50 layers that includes multiple convolutional (Conv) and fully connected (FC) layers. The model extracts features from the images and grades their severity. Finally, the output categorizes the images into three classes: Normal, Moderate, and Severe. The arrows in the diagram indicate the sequential flow of the data from the dataset through pre-processing, feature extraction using the ResNet-50 Model, and classification.

between 0 and 1 and sum to 100%. Mathematically, for a vector $\mathbf{z}$ of logits, the softmax function is defined as:

$$\text{Softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{10}$$

where K is the number of classes and z_i is the i-th logit.

6 Experimental Result

The proposed ResNet-50 model demonstrated superior classification accuracy, achieving 97.56% for full Cataract images and 95.23% for partial Cataract images showing Table 4. The model was trained with different epoch numbers, with the highest accuracy obtained after 180 iterations of 5 epochs. The validation accuracy and validation loss of the proposed model are illustrated in Figure 7. In terms of accuracy, precision, recall, specificity, and F1-score, the suggested model outperformed other pre-trained models. The model showed exceptional performance across dataset splits, achieving an accuracy of 97.56% for full Cataract images and 95.23% for partial Cataract images, outperforming previous models by 40%, 40% and 20%, respectively - comparative analysis of model characteristics that show the efficiency and lower time complexity of the proposed ResNet-50 model.

In Table 5, In comparison to leading models, the current model's performance is evaluated in terms of accuracy, precision, recall, and specificity. In all the evaluation measures for data set splitting, the suggested technique delivered good performance and took the top spot. With an accuracy of 97.56% full Cataract images and 95.23% partial Cataracts, Showing in Table 4 this technique surpasses previous pre-trained models for dataset splitting by 40%, 40%, and 20%.

6.1 In terms of time and space complexity

The suggested model shows the lowest time complexity and greater performance compared to the other networks' model attributes, such as depth, average running time, total layers, trainable parameters, and size. Compared to other pre-trained models, it significantly reduces the model size and trainable parameters to 19.78 MB and 1.17 MB, respectively.

This comprehensive evaluation offers a nuanced understanding of the proposed model's performance, comparing it to state-of-the-art methods and highlighting its effectiveness in cataract detection and classification. The confusion matrix further breaks down the model's predictive metrics, offering valuable

Table 4. Comparison of various approaches for cataract detection.

Approaches	Year	Methods	Dataset Size	Accuracy
Gao et al. [42]	2011	Texture analysis	4545	84.8%
Guo et al. [30]	2015	Wavelet transformation	445	90.9%
Fuadah et al. [43]	2015	Texture analysis & KNN	160	94.5%
Yang et al. [31]	2016	SVM & NN	1239	93.2%
Harini et al. [26]	2016	SVM	-	93.33%
Zhang et al. [44]	2017	Deep CNN	5620	93.52%
Ran et al. [45]	2018	RF & DCNN	5408	90.69%
Pratap et al. [32]	2019	AlexNet & SVM	800	92.91%
Sigit et al. [46]	2019	Single-layer perceptron	50	85%
Cao et al. [25]	2020	NN	1355	94.83%
Hossain et al. [28]	2020	ResNet-50	4000	95.77%
Khan et al. [47]	2021	VGG-19	1400	97.47%
Lahmar & Idri [48]	2022	DenseNet201, MobileNet_V2	3662, 35126	85.79%, 93.09%
Pan et al. [49]	2023	Inception V3, ResNet-50	705, 650	93.81%, 91.76%
Puchaicela-Lozano et al. [50]	2023	R-CNN, ResNet-50	1032	95%
Proposed Method (Partial Image)	2024	ResNet-50	17500	**95.23%**
Proposed Method (Full Image)	2024	ResNet-50	17500	**97.56%**

Table 5. Comparison of the Proposed Method to other State-of-art.

S.NO	References	Methodology	Accuracy	Sensitivity	Precision	Specificity
1	Junayed et al. [4]	Cataract Net	95.02%	95.76%	94.86%	94.85%
2	Pratap et al. [32]	Alex NetSVM	92.87%	92.88%	93.04%	93.04%
3	Xiong et al.[51]	Decision Tree	92.80%	93.01%	93.03%	92.01%
4	Hossain et al. [28]	DCNN, ResNet	95.77%	94.43%	94.43%	98.07%
5	Harini et al. [26]	SVM, RBFN	91.11%	90.00%	91.04%	93.33%
6	Bragança et al. [52]	Comparison of CNN	0.905%	0.850%	0.955%	0.960%
7	Li et al. [53]	CNN	96.2%	0.954%	-	0.967%
8	**Proposed Method Partial Images**	**ResNet-50**	**95.23%**	**96%**	**95.13%**	**95.23%**
9	**Proposed Method Full Images**	**ResNet-50**	**97.56%**	**100%**	**96.41%**	**96.63%**

insights into its true-positive and false-positive rates.

6.2 Comparative Analysis

This section offers a comparative review of several research in the domains of machine learning , image processing. and deep learning-based cataract detection, with a particular focus on their reported accuracy scores, as outlined in Table 5.

Several studies leveraged image processing techniques for Cataract detection, including Guo et al. [13], Fuadah et al. [33], and Gao et al.[42]; their approaches achieved commendable accuracy rates of 94.5%, 90.9%, and 84.8%, respectively. On the other hand, machine learning-based classifiers were employed by Cao et al. [25], and Bhanumathi [26], demonstrating successful Cataract identification with detection accuracies of 93.2%, 93.33%, and 94.83%, respectively. In the realm of deep learning, Hossain et al. [28], Pratap and Kokil [32], Zhang et al. [22], and Ran et al. [45] proposed approaches with reported precision of 95.77%, 92.91%, 93.52% and 90.69%, respectively. It is crucial to note that these methods operated on proprietary data sets that were not publicly accessible, using complete images of cataract disease. Consequently, the accuracy metrics may vary across different datasets.It is crucial to construct and evaluate these models on a shared dataset in order to give an equitable comparison with the most recent techniques.In our evaluation, we are constrained by the availability of the Kaggle dataset for comparison, comprising 3500 images. The proposed deep learning-based ResNet-50 model exhibits superior performance, achieving an accuracy of 97.56% Showing the results in Figure 8.This performance is noteworthy considering the consistent use of the data set for a fair comparison. The

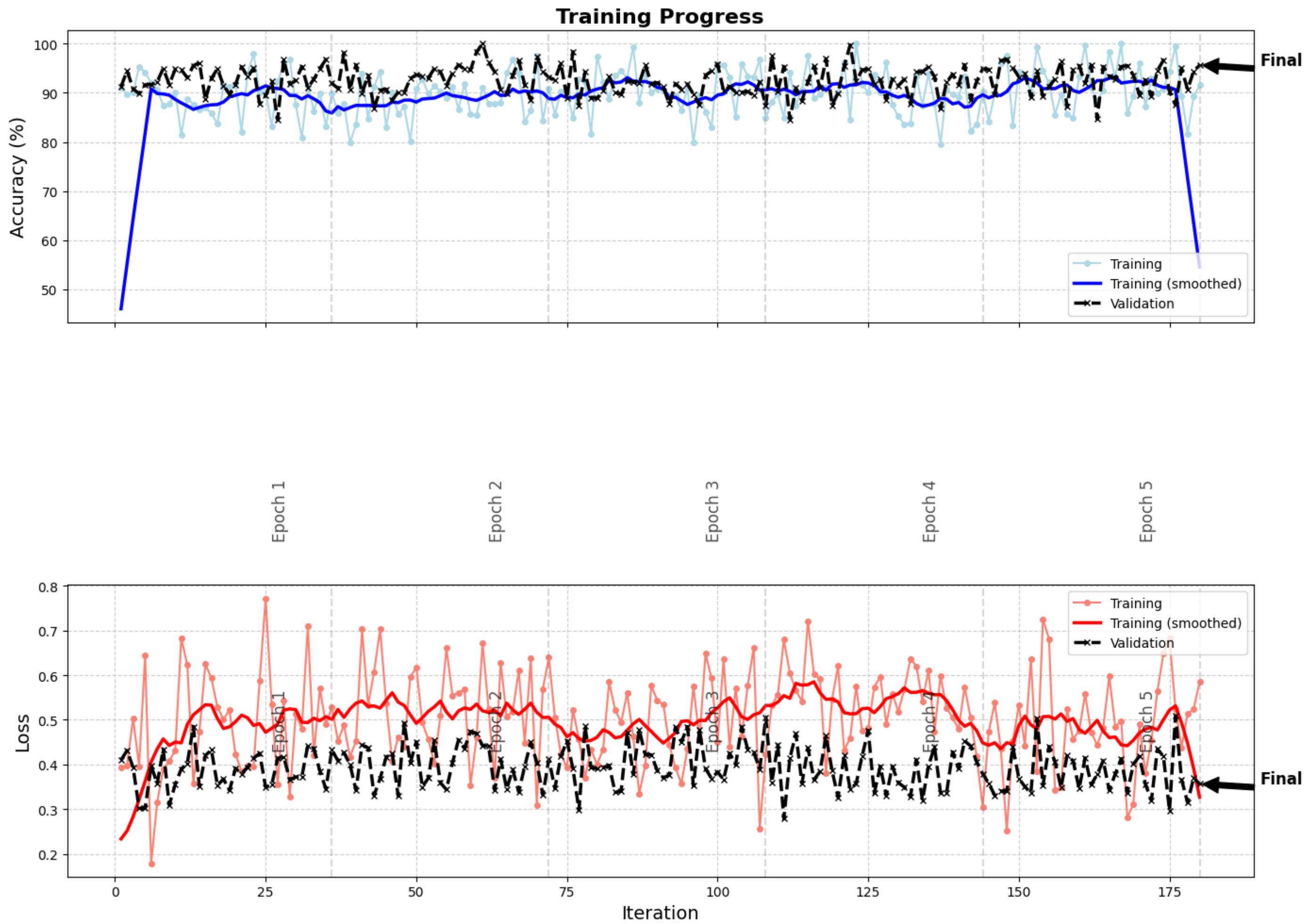


Figure 7. The training progress diagram shows the model performance over the training period through accuracy and loss trends. The top plot shows accuracy, with the Y-axis representing accuracy percentage and the X-axis representing iterations. It features a light blue line for training accuracy, a dark blue line for smoothed training accuracy, and black crosses for validation accuracy, ending with a "Final" accuracy marker. The bottom plot illustrates loss, with the Y-axis for loss values and the X-axis for iterations. It includes a red line for training loss, a dark red line for smoothed training loss, and black crosses for validation loss, concluding with a "Final" loss marker. Both plots are segmented by vertical dashed lines indicating the end of each epoch, labeled from Epoch 1 to Epoch 5. These diagrams Provide a comprehensive overview of the model's learning progress during training.

proposed model's performance is also highlighted in Table 4 alongside other pre-trained CNN models, emphasizing both its efficiency and cost-effectiveness.

It's noteworthy that our approach involved augmenting the training dataset, resulting in a larger dataset compared to many previous studies. This augmentation was a strategic measure to prevent overfitting and enhance the model's generalization capabilities. In general, our findings showcase the ResNet-50 model as a robust and effective solution for cataract detection, offering improved accuracy within a standardized dataset and setting the stage for potential real-world applications. In addition, this system can detect partial images where 30% of the image is not present and 70% of the image is present. It still can perform better in that case, well, giving an accuracy of 95.23%. This simply means that 70% of the image will cover more infected areas, leading to better accuracy. This model also performs well on images like 75%, 80%, and 85% or higher, and all the results will have an accuracy of 95% or higher. Particularly for people in remote locations, these non-invasive techniques are Beneficial. Better feature extraction methods are also required in addition to the classification algorithms. The Cataract is assessed using very accurate CNN-based feature extraction techniques.

6.3 Discussion

This capability proves valuable for cataract classification and identification, offering crucial

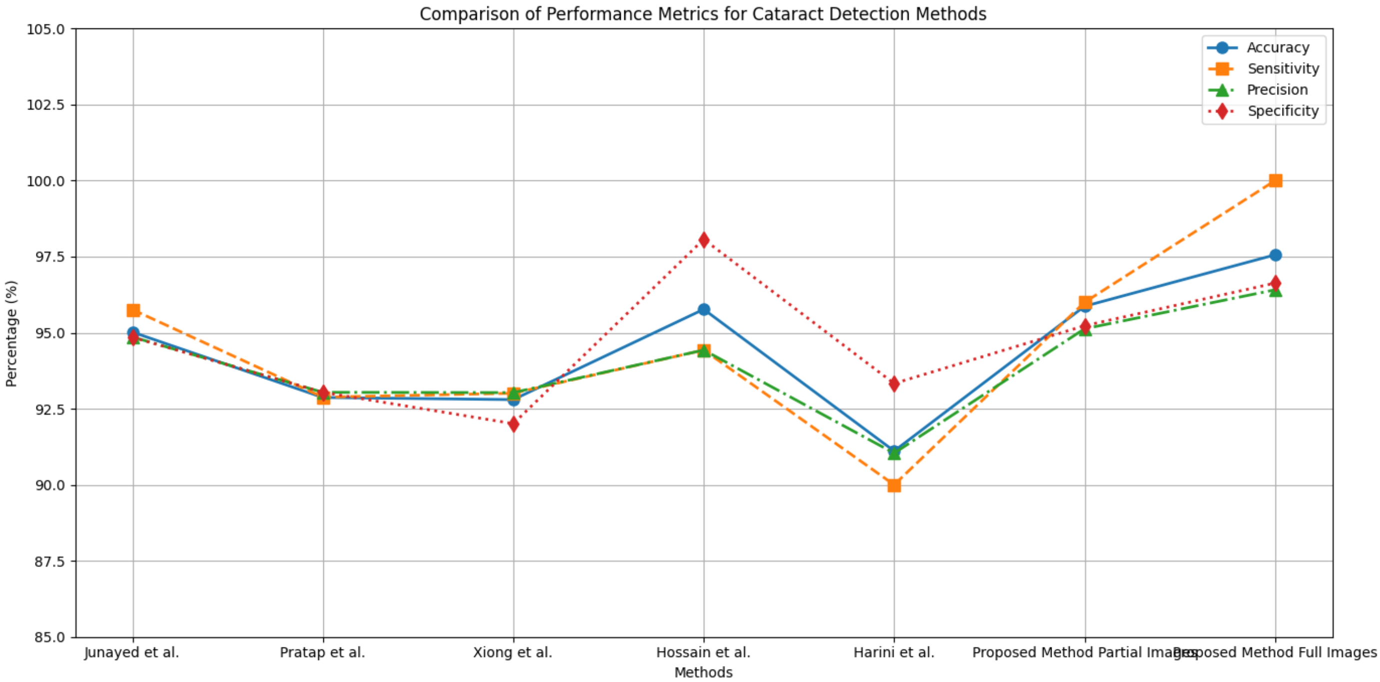


Figure 8. The graph shows a comparative analysis of performance metrics for various cataract detection methods, including the proposed ResNet-50 method for both partial and full images. The metrics compared are accuracy, sensitivity, precision, and specificity across different studies. The proposed method with full images demonstrates superior performance across all metrics compared to the other methods evaluated.

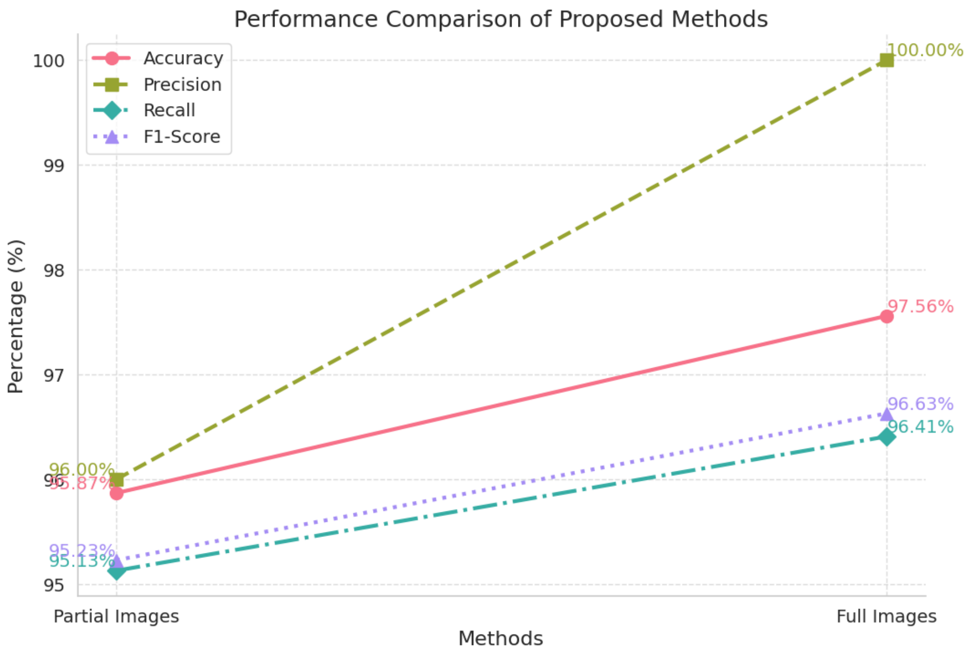
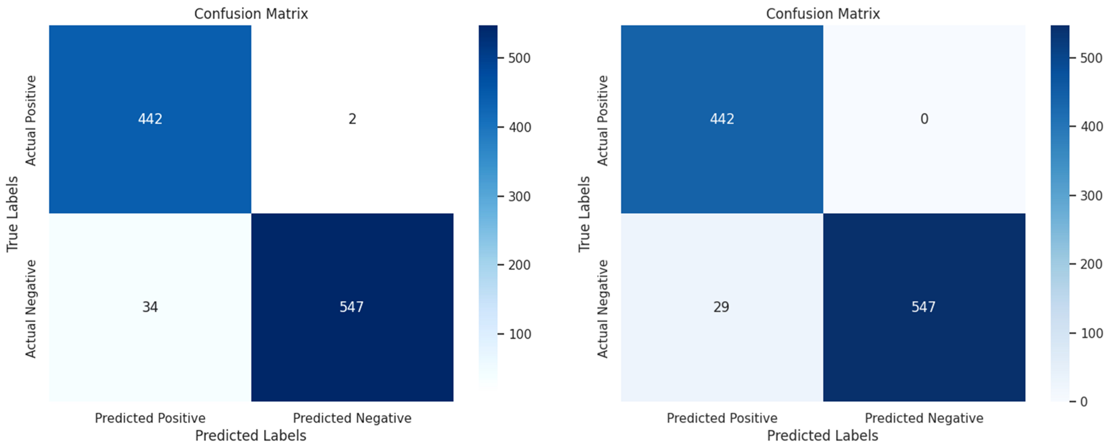


Figure 9. The graph compares the performance metrics of the ResNet-50 method on cataract detection using full images versus partial images. The metrics displayed include accuracy, precision, recall, and specificity. The results show that using full images significantly improves performance across all metrics compared to using partial images.

support to ophthalmologists in their diagnostic endeavors. In addition, the system demonstrated efficacy in detecting partial images, where only 70% of the image is present, achieving an accuracy of 95.23%. This is shown in Figure 9 and confusion matrix in Figure 10. This suggests that a higher coverage of the infected areas leads to improved accuracy, making the model adaptable to varying degrees of image completeness, such as 75%, 80%, and 85% or above.



(a): Confusion Matrix Partial Images **(b): Confusion Matrix Full Images**

Figure 10. The image shows two confusion matrices illustrating the performance of ResNet-50 on Partial Images and Full Images of cataracts diseases.

7 Conclusion

In this study, we introduced a straightforward yet powerful deep learning-based automatic Cataract diagnostic technique named ResNet-50. Leveraging fundus images from the Cataract dataset, we meticulously pre-processed, organized, and augmented the dataset. As part of our exploration of ResNet-50, In order to strike a compromise between computational effectiveness and model correctness, we looked at a number of factors, including optimisation techniques, activation functions, loss functions, and different layers. The ResNet-50 model demonstrated remarkable performance, surpassing state-of-the-art cataract detection approaches with an impressive accuracy of 97.56%. Additionally, the model exhibited excellence in recall (100%), precision (96.41%), and specificity (96.63%) Showing graphical in Figure 8. The high accuracy, coupled with cost and time efficiency, empowers ophthalmologists to diagnose Cataract disease earlier and with increased accuracy. A notable feature of our system is its ability to distinguish between various grading levels, including normal, moderate, and severe Cataracts.

We are still unable to identify the precise location of the infected part of the Cataract disease in eye, which limits our work. Further, it has not been very successful in locating the edges of the infected area. Looking ahead, future work can involve ranking diseases based on their intensity or severity. Although this study focused on fundus images, we envision extending our approach to ordinary images captured by consumer-level cameras. The goal is to create an early detection system that works seamlessly with low-end cameras in handheld devices, such as mobile phones. This advancement has the potential to revolutionize the identification of eye disorders, serving as an accessible and widespread early warning and detection system that is particularly beneficial for individuals in remote locations. In the future, the disease can be ranked according to intensity or severity. Fundus images are used in this work; however, in the future, this work will be extended to normal images taken by ordinary cameras so that an early detection system can be designed at the consumer level. Suppose this system can work with the ordinary low-end camera in any hand-held device (mobile, for example). In that case, many applications can be developed to identify any disorder in the eye. They can be used as early warning and detection systems.

Conflicts of Interest

The authors declare no conflicts of interest.

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