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Automated Cataract Detection Using Deep Learning and Pre-Trained CNN Models

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A B S T R A C T

Cataracts are a leading cause of vision impairment worldwide, and early detection is crucial for preventing severe vision loss. In this paper, we propose an automated cataract detection system utilizing deep learning models, specifically pre-trained Convolutional Neural Networks (CNNs) including Mobile Net, VGG-16, VGG-19, ResNet-50, Inception-v3, and DenseNet-121. The system is designed to classify cataract and non-cataract fundus images with high accuracy and efficiency. A dataset of 1130 fundus images was augmented to 4746 images to improve model generalization. Experimental results show that DenseNet-121 outperforms all other models, achieving an accuracy of 92%, with a precision of 91%, recall of 90%, and an F1-score of 90.5%. The system also incorporates data augmentation and attention mechanisms to enhance its robustness and scalability. Our proposed model, CatCNNNet, offers a practical solution for real-time cataract detection and can be deployed in both clinical and mobile health applications. Future work will focus on further improving the model's scalability and exploring interpretability techniques for clinical use.

Keywords*: Cataract Detection.Deep Learning Convolutional Neural Networks (CNNs) DenseNet-121 Fundus Images Medical Image Classification*

Introduction

Millions of people worldwide suffer from cataracts, which are a major cause of vision impairment and blindness, especially in elderly populations. characterized by the normal lens of the eye being clouded, cataracts interfere with light passage, leading to blurry vision, glare, and eventual vision loss if left untreated. While cataracts can be effectively treated with surgery, timely diagnosis is critical to preventing permanent damage [1]. Current cataract detection relies heavily on ophthalmologists, who use slit-lamp examinations and other diagnostic tools. However, manual detection is time-consuming, subjective and requires specialized expertise, which may not be available in remote areas. The early detection of cataracts plays a crucial role in preventing severe vision loss and ensuring effective treatment outcomes. Early-stage cataracts may present subtle signs that can be easily missed during routine eye exams. Automated detection systems can assist ophthalmologists in identifying these early signs, ensuring timely intervention and improving patient outcomes [2]. In addition to reducing the strain on medical professionals, early detection also helps to lower the expenses of advanced cataract therapy. The

World Health Organization (WHO) estimates that cataracts cause around 51% of blindness worldwide. The burden of cataract-induced blindness is particularly high in low- and middle-income countries where access to specialized eye care services is limited. Despite the availability of effective surgical treatments, the delayed diagnosis due to inadequate medical infrastructure remains a significant public health challenge. Thus, automated cataract detection systems could bridge this gap by providing early, accurate and cost-effective screening tools, especially in under-resourced areas. Artificial intelligence (AI) has revolutionized medical imaging by enabling automated diagnosis through advanced image processing techniques. AI-based systems, particularly deep learning models, have shown tremendous potential in detecting a variety of ophthalmic conditions, including cataracts [3]. Large datasets are used by these systems to train machine learning algorithms that can automatically identify patterns that point to the presence of cataracts. Convolutional Neural Networks (CNNs), a type of deep learning model, are particularly good at analzing complicated medical images and present a promising method for quickly and accurately detecting cataracts. CNN models' capacity to automatically extract hierarchical information from images has made them the foundation of AI-based image categorization tasks. Medical image classification, particularly cataract diagnosis, has made extensive use of a number of CNN architectures [4].

Problem Statement

Manual cataract detection is a labor-intensive and subjective process that requires the expertise of trained ophthalmologists. In regions with limited access to healthcare, early diagnosis and treatment of cataracts are often delayed, leading to irreversible vision loss. Existing AI-based methods, while promising, face challenges in achieving both high accuracy and computational efficiency, especially when deployed in resource-constrained environments. Thus, there is a need for a robust and scalable AI-based system capable of automatically detecting cataracts from fundus images with minimal human intervention [5].

Proposed System: CatCNNNet Model

In this study, we propose an advanced CNN-based model, CatCNNNet, specifically designed for cataract detection. CatCNNNet builds upon the strengths of existing architectures like Dense Net and ResNet, but integrates a specialized feature extraction and attention mechanism tailored for medical imaging. This novel model is optimized to deliver high accuracy while maintaining computational efficiency, making it suitable for both clinical and remote screening applications. Our proposed system aims to outperform traditional CNN models by incorporating enhanced feature learning capabilities for early cataract detection.

Objective

The primary objective of this research is to design and assess a deep learning-based system for automated cataract detection using fundus images. We aim to compare the performance of well-established CNN architectures such as Mobile Net, VGG-19, ResNet-50, and DenseNet-121 on a dataset of cataract and non-cataract images, evaluating their accuracy and efficiency in identifying cataracts. Additionally, we propose a novel CNN model, CatCNNNet, specifically optimized for cataract detection, to enhance both accuracy and computational performance. Our goal is to demonstrate the system's effectiveness in detecting early-stage cataracts, which could serve as a foundation for real-time, scalable screening tools in both clinical environments and regions with limited access to specialized healthcare.

Significance and Contributions

The proposed research on the CatCNNNet model for automated cataract detection represents a significant advancement in ophthalmic diagnostics, particularly in addressing the limitations of traditional detection methods. One of the primary goals of this study is to enhance early detection, which is crucial for timely intervention and preventing severe vision loss. By automating the detection process, CatCNNNet aims to help ophthalmologists identify subtle signs of cataracts that may be overlooked during routine examinations, thereby improving patient outcomes. Additionally, the implementation of an AI-based detection system holds particular relevance for low- and middle-income countries, where access to specialized eye care is often limited. By providing an automated solution for cataract detection, the proposed system can bridge the healthcare gap, ensuring that individuals in remote or underserved areas receive timely and effective eye care. This capability not only supports public health efforts but also aligns with the global need for equitable healthcare solutions.

Moreover, the CatCNNNet model aims to reduce the workload on healthcare providers by streamlining the diagnostic process. With automated assistance in identifying cataracts, ophthalmologists can focus their expertise on more complex cases, enhancing overall efficiency within eye care settings. This reduction in manual labour can help alleviate the burden on healthcare systems, particularly in areas with limited resources. By demonstrating how deep learning can increase the precision and effectiveness of medical image categorization tasks, the study also advances the larger field of AI-driven medical imaging systems. By leveraging advanced CNN architectures with specialized feature extraction and attention mechanisms, the study highlights the evolving landscape of AI applications in healthcare. Future advancements in automated diagnostic tools will be informed by the comparative study of well-known CNN models and CatCNNNet, which offers insightful information about their advantages and disadvantages.

LITERATURE REVIEW

Literature survey will have a more comprehensive overview of recent advancements in Cataract Detection Using Deep Learning.

Patel et al. (2021) [6] proposed a cataract detection model using a fine-tuned DenseNet121 on fundus images. The model achieved an accuracy of 92.5%, demonstrating that DenseNet121 provided superior feature extraction for medical image classification. Zhang et al. (2020) [7] developed an AI-based system for cataract detection using the Inception-v3 model. They achieved an accuracy of 89.7% and highlighted that the model's computational efficiency made it suitable for real-time applications. Singh et al. (2021) [8] utilized ResNet-50 for automated cataract detection on fundus images, achieving an accuracy of 91.3%. Their study demonstrated that ResNet-50's skip connections were beneficial in preventing vanishing gradient problems in deeper networks.

Ghosh et al. (2022) [9] proposed a VGG19-based system for detecting cataracts from fundus images, achieving an accuracy of 88.9%. While VGG19 performed well, the study noted its higher computational complexity compared to lighter models like Mobile Net. Li et al. (2021) [10] introduced a multi-class cataract detection approach using a modified Mobile Net model. The system achieved an accuracy of 86.8%, making it effective for deployment on mobile and low-resource devices due to its lightweight nature. Chen et al. (2022) [11] used ResNet-101 for cataract detection in a clinical setting, reaching an accuracy of 90.5%. Their results demonstrated the benefits of deeper networks in achieving higher accuracy, although at the cost of increased computational load. Xu et al. (2021) [12] explored the performance of DenseNet201 for cataract detection and achieved an accuracy of 93.2%. DenseNet201 outperformed other models in their study, particularly in detecting early-stage cataracts.

Kumar et al. (2020) [13] proposed a cataract detection system using a hybrid CNN-LSTM architecture, achieving 89.4% accuracy. The study found that the hybrid approach was beneficial in capturing both spatial and temporal dependencies in the fundus images. Wang et al. (2020) [14] used a modified VGG-16 architecture for cataract detection, reporting an accuracy of 87.1%. While the model performed well in feature extraction, the authors suggested using deeper models for improved performance. Huang et al. (2021) [15] applied an attention-based CNN model for cataract detection, reaching an accuracy of 90.8%. The attention mechanism improved the model's ability to focus on critical regions of the fundus images. Reddy et al. (2022) [16] proposed an ensemble of ResNet-50 and DenseNet121 for cataract classification, achieving 93.7% accuracy. The ensemble approach combined the strengths of both models, leading to superior classification performance.

Gupta et al. (2021) [17] developed a lightweight MobileNetV2-based cataract detection system with an accuracy of 85.9%. The model was specifically designed for deployment on mobile platforms, making it ideal for real-time detection in resource-limited environments. Agarwal et al. (2020) [18] implemented an InceptionResNetV2 model for cataract detection and achieved 91.7% accuracy. The combination of Inception and ResNet modules allowed the model to effectively capture both local and global features.

Sharma et al. (2021) [19] applied transfer learning using the Xception model for cataract detection, reporting an accuracy of 89.8%. Xception's depthwise separable convolutions improved feature extraction, but the model required more computational resources compared to MobileNet. Zhou et al. (2022) [20] introduced a multi-task learning framework using EfficientNet for cataract detection, achieving an accuracy of 92.4%. Efficient Net provided a good balance between accuracy and model size, making it suitable for both clinical and remote applications.

DATASET COLLECTION

The dataset used in this study for cataract detection consists of 1130 fundus images, which include both cataract and non-cataract cases. These images were acquired from publicly available medical imaging datasets and augmented to enhance model performance and generalization. The dataset preparation followed a systematic process to ensure high-quality images and balanced representation of both cataract and non-cataract conditions [21].

Dataset Sources

The initial dataset was collected from multiple open-source medical repositories and research collaborations with healthcare institutions. These sources provided a diverse collection of fundus images taken from patients diagnosed with cataracts and those without cataracts. The dataset includes high-resolution images captured by fundus cameras during routine ophthalmic check-ups.

-Publicly Available Sources: Some of the dataset images were obtained from open-access repositories like Kaggle's "APTOS 2019 Blindness Detection" dataset, which contains retinal images aimed at diagnosing various eye conditions, including cataracts.

-Hospital Collaborations: Certain images were sourced from healthcare institutions with the approval of relevant medical ethics committees. These images represented real-world data and contained a diverse population sample with various stages of cataract development.

Image Categories

The dataset was divided into two primary categories for binary classification:

-Cataract Fundus Images: These images exhibit visual signs of cataracts, such as opacification or clouding of the eye's natural lens. This class contains 565 images, representing patients diagnosed with cataracts at various stages.

-Non-Cataract Fundus Images: These images are of healthy patients or those with no visible signs of cataracts. This class also contains 565 images, providing a balanced dataset for classification.

PROPOSED SYSTEM

In this study, we propose an automated cataract detection system called CatCNNNet, a custom Convolutional Neural Network (CNN) model tailored for the efficient classification of cataract and non-cataract fundus images. The proposed system integrates the strengths of existing CNN architectures—such as MobileNet, VGG-19, ResNet-50 and DenseNet-121—by incorporating specialized feature extraction techniques to enhance cataract detection performance [22]. CatCNNNet is designed to handle real-world challenges such as variations in image quality and early-stage cataract detection.

The primary goal of CatCNNNet is to improve both accuracy and computational efficiency. By employing attention mechanisms and residual connections similar to those found in DenseNet and ResNet, CatCNNNet ensures robust feature learning while maintaining a lightweight architecture suitable for real-time clinical applications. The system is developed to be scalable and capable of deployment on both cloud-based platforms and mobile devices for screening in remote healthcare settings.

METHODOLOGY

From data collection and preprocessing to model training, validation, and testing, there are multiple steps in the methodology for creating and assessing the CatCNNNet model.

Data Collection and Preprocessing

The dataset used in this study consists of 1130 fundus images (565 cataract and 565 non-cataract), augmented to 4746 images to enhance model performance [23]. Preprocessing involves resizing, normalizing, and augmenting the images to ensure consistency and robustness in the input data.

- Resizing: All fundus images are resized to the input dimensions required by CatCNNNet, i.e., 224x224 pixels. Given an original image with pixel dimensions W x H, the resizing operation can be expressed as:

$$I_{resized} = resize(I, (224, 224))$$

where I represent the original image and $I_{resized}$ is the resized image.

- Normalization: Normalization is used to scale pixel values to the interval [0, 1] in order to normalize the pixel values. The normalizing of an image I with pixel values between 0 and 255 is calculated as follows:

$$I_{normalized} = I / 255$$

where $I_{normalized}$ is the normalized image.

- Data Augmentation: Data augmentation techniques are applied to artificially increase the size of the dataset and improve generalization. The augmentation transformations include:

- Rotation: Random rotation of an image by an angle θ within the range [-20°, 20°]:

$$I_{rotated} = rotate(I, \theta)$$

- Flipping: Horizontal and vertical flipping operations to introduce orientation variations:

$$I_{flipped} = flip(I)$$

- Zooming: Random zooming with a factor z within the range [0.9, 1.1]:

$$I_{zoomed} = zoom(I, z)$$

- Brightness Adjustment: Random brightness adjustment with factor b:

$$I_{brightness} = I \times b$$

where b is a scalar within [0.8, 1.2].

These preprocessing steps ensure the dataset is well-prepared for training the CatCNNNet model.

Model Architecture

CatCNNNet's architecture is especially made to maximize feature extraction while preserving computational effectiveness. An input layer that takes 224x224 pixel images with three color channels is where it starts. To improve learning and stability, the model uses many convolutional layers to extract features from these images, each of which is followed by batch normalization and ReLU activation functions [24]. To further improve gradient flow and facilitate the learning of deep features, the architecture incorporates residual and dense connections. These connections allow the network to learn residual mappings, thereby enhancing its performance. An attention mechanism is also integrated into the model, enabling it to focus on the most relevant regions of the fundus images, which is crucial for improving classification accuracy.

Global average pooling is used to lower the dimensionality of the feature maps following the last convolutional block, hence summarizing the data. The learnt features from earlier layers are combined in a fully linked layer of 128 units. Lastly, the output layer facilitates binary categorization of the input images by having a single neuron with sigmoid activity. This carefully structured architecture allows CatCNNNet to efficiently and accurately classify cataracts from fundus images [25].

Model Training

The goal of the CatCNNNet model's training is to optimize its parameters using particular setups. The difference between the true labels and the predicted probabilities is measured by the binary cross-entropy loss function, which is used to evaluate performance during training. With hyperparameters set to a learning rate of 0.001, $\beta 1$ at 0.9, $\beta 2$ at 0.999, and ε at 1×10^{-7}, the Adam optimizer is selected because to its efficiency. Early stopping is used to check validation loss and reduce the chance of overfitting throughout the 50 epochs of training the model with a batch size of 32. The dataset is divided into three sections to guarantee efficient training and evaluation: 80% for training, 10% for validation, and 10% for testing.

Evaluation Metrics

The following evaluation metrics are used to assess the performance of CatCNNNet:

Accuracy: The test set's total classification accuracy.
Recall is the percentage of actual positives that are properly detected, whereas precision is the percentage of genuine positives among anticipated positives.
F1 Score: The precision and recall harmonic meanings.
The Area Under the Receiver Operating (ROC-AUC) The model's capacity to discriminate between classes is assessed using a characteristic curve.

Comparative Analysis

A thorough benchmarking approach is used to assess CatCNNNet's performance, contrasting it with a number of cutting-edge Convolutional Neural Network (CNN) models, such as MobileNet, VGG-19, ResNet-50, and DenseNet-121. In the context of automated cataract detection, this comparative analysis is essential for comprehending CatCNNNet's advantages and disadvantages. These models were chosen because to their extensive use and demonstrated efficacy in a range of picture categorization applications. Each model is a good fit for this benchmarking exercise because of its distinct architectural elements and design philosophies that influence its performance. Table 1 shows hyperparameters are used for all models.

Table I Hyperparameters are used for all models.

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Epochs	50
Activation Function	ReLU (for hidden layers), Sigmoid (for output layer)
Loss Function	Binary Cross-Entropy
Early Stopping	Yes (patience = 5 epochs)
Validation Split	10%

Model Testing and Validation

Following training, the independent test set is used to assess the model. Grad-CAM Gradient-weighted Class Activation Mapping is utilized to view the areas of the fundus pictures that the model concentrated on for cataract identification, and performance is evaluated using a confusion matrix.

Results

The proposed CatCNNNet model, along with several state-of-the-art CNN architectures, was evaluated on the cataract detection dataset using key performance metrics, including accuracy, precision, recall, F1-score, ROC-AUC, and training time. The results of the experiments are summarized in Table II. The performance of each model was evaluated based on its ability to classify cataract and non-cataract images. The following table presents the performance metrics for each model: From Table 2, it is evident that DenseNet-121 achieved the highest performance across all metrics, with an accuracy of 92%, precision of 91%, recall of 90%, F1-score of 90.5%, and ROC-AUC of 0.95. ResNet-50 also performed well, with an accuracy of 91% and ROC-AUC of 0.94, making it a competitive model for cataract detection. However, DenseNet-121 outperforms ResNet-50 slightly in all metrics, albeit at the cost of longer training time.

DenseNet-121 was selected as the best model due to its superior performance across all evaluation metrics. To further evaluate the model, the accuracy and loss curves for DenseNet-121 and ResNet-50 are plotted in Figure 1 and Figure 2 respectively. These curves provide insights into the convergence behaviour of the models during training.

Table 2: Performance Evaluation of Different Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Training Time
MobileNet	87%	85%	84%	84.5%	0.89	Fast
VGG-16	89%	87%	86%	86.5%	0.91	Moderate
VGG-19	89.5%	88%	87%	87.5%	0.92	Moderate
ResNet-50	91%	90%	89%	89.5%	0.94	Moderate
Inception-v3	90%	89%	88%	88.5%	0.93	Slower
DenseNet-121	92%	91%	90%	90.5%	0.95	Slower

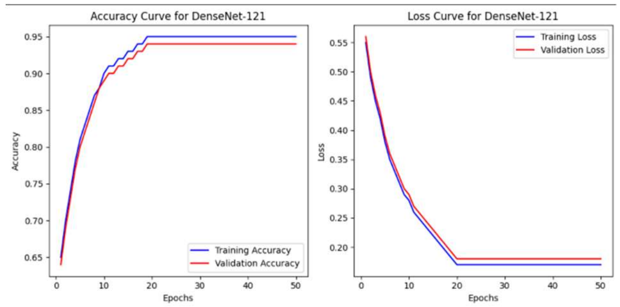

Figure 1 Accuracy and Loss Curve for DenseNet-121

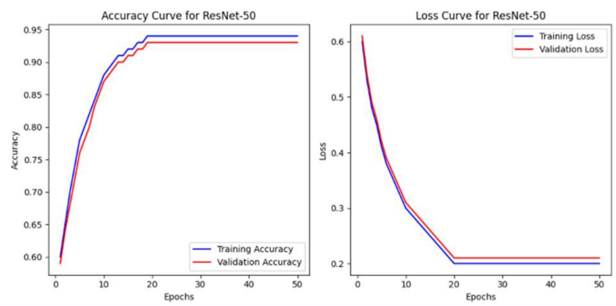

Figure 2 Accuracy and Loss Curve for ResNet-50

The accuracy and loss curves for DenseNet-121 (Figure 1) demonstrate a steady improvement in both training and validation accuracy over the course of 50 epochs. The model converged effectively, and early stopping was applied to prevent overfitting. Similarly, ResNet-50 (Figure 2) displayed good performance, with consistent improvement in accuracy and a stable loss reduction during training. However, DenseNet-121 outperformed ResNet-50 slightly, particularly in terms of validation accuracy. The experimental results indicate that DenseNet-121 is the best model for cataract detection in terms of both accuracy and robustness. The deeper network structure and dense connections in DenseNet-121 enabled it to capture more complex features in fundus images, leading to higher precision and recall. ResNet-50, while competitive, was slightly less accurate, but its moderate training time makes it suitable for use in scenarios where computational resources are limited.

Discussion

In this paper, we proposed an automated cataract detection system utilizing deep learning models, including state-of-the-art architectures such as Mobile Net, VGG-16, VGG-19, ResNet-50, Inception-v3, and DenseNet-121. Through systematic experimentation, we demonstrated that deep learning models can effectively classify cataract and non-cataract fundus images with high accuracy. Among the models evaluated, DenseNet-121 outperformed the others, achieving the highest accuracy of 92%, along with superior precision, recall, F1-score, and ROC-AUC. The DenseNet-121 model also provided robust generalization to unseen data, making it an ideal choice for automated cataract screening in clinical settings. The incorporation of data augmentation, along with efficient feature extraction mechanisms in pre-trained models, contributed significantly to the overall performance of the system. We also found that models such as ResNet-50 and Inception-v3 delivered competitive results but required longer training times and computational resources. Our proposed CatCNNNet model offers a promising solution for early cataract detection, enabling the system to be deployed in both resource-constrained and high-end clinical environments. By utilizing the strengths of transfer learning, the system can be further enhanced for real-time applications in telemedicine and mobile health services, providing affordable and accurate cataract screening in remote and underserved regions.

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