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Automatic Detection of High Myopia and Pathological Myopia Using Fundus Image

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Abstract

Abstract—Myopia, particularly high myopia (HM) and pathological myopia (PM), has become a growing global concern, especially among the younger population. Early and accurate detection is essential to prevent irreversible vision loss caused by progressive retinal damage. This paper presents an automated diagnostic system for classifying fundus images into normal, high myopia, and pathological myopia categories using deep learning techniques. The proposed method involves preprocessing steps for image enhancement, feature extraction using DenseNet121, and classification using a three-class architecture. Comparative evaluation with models such as VGG16, GoogleNet, and standard CNNs revealed that DenseNet121 achieved the best performance, with 94% accuracy and an F1-score of 92. The system also incorporates a user-friendly graphical interface and database integration for real-world deployment. This research demonstrates the viability of using deep learning to support ophthalmologists in early diagnosis and long-term patient monitoring, especially in remote or resource-constrained settings.

Keywords: High Myopia, Pathological Myopia, Fundus Image, DenseNet121, Deep Learning, CNN, Medical Image Classification, Automated Diagnosis

1. INTRODUCTION

Myopia, commonly known as nearsightedness, is one of the most prevalent refractive disorders affecting vision across all age groups. However, over the past decade, there has been a significant surge in cases of high myopia (HM) and pathological myopia (PM), particularly among the youth. Factors such as prolonged screen time, limited outdoor exposure, and digital lifestyle changes have contributed to this alarming trend. High myopia is characterized by severe elongation of the eyeball, while pathological myopia involves progressive structural degeneration of the retina, potentially leading to irreversible vision loss, retinal detachment, or myopic macular degeneration.

Early detection and classification of HM and PM are crucial to prevent complications through timely medical intervention. Traditional diagnostic methods, including manual examination and subjective refraction, are often time-consuming, prone to human error, and limited by the availability of trained ophthalmologists. Fundus photography, which captures detailed images of the retina, presents an effective modality for non-invasive eye screening.

In this context, artificial intelligence and deep learning—specifically Convolutional Neural Networks (CNNs)—offer promising avenues for automating myopia detection. This paper proposes an automated system based on DenseNet121 for classifying fundus images into three categories: normal, high myopia, and pathological myopia. The system emphasizes robust preprocessing, efficient feature extraction, and real-time classification, ultimately providing scalable and accessible support for healthcare providers.

(a) normal fundus (b) high myopia (c) pathological myopia

Figure No. 1: Class

2. LITERATURE REVIEW

Several research efforts have explored the use of deep learning models for automatic detection and classification of myopia using fundus images. The increasing availability of retinal imaging datasets and improvements in convolutional architectures have accelerated progress in this field.

Himami et al. [1] employed ResNet-50 and DenseNet-201 to classify fundus images for pathological myopia detection. Their study highlighted the performance benefits of DenseNet-201, which achieved 97% accuracy and 100% specificity when optimized with the Adam optimizer. Preprocessing steps such as normalization, image resizing, and data augmentation significantly contributed to model robustness.

In a separate work, Kumari and Saxena [2] introduced a custom CNN called PMnet, designed for myopia detection and visualization. Their model used an autoencoder for feature extraction and employed Cyclic Learning Rate (CLR) optimization to improve convergence speed. They also introduced saliency maps for visual interpretation, though their classification was limited to binary outputs (normal vs. pathological).

Narayanan et al. [3] proposed a novel safety-focused approach where image processing and CNNs were used to screen drivers for myopia. Their methodology incorporated GLCM and GLRLM texture extraction techniques followed by CNN classification, achieving up to 97% accuracy. However, it was limited to detecting general myopia, not distinguishing between HM and PM.

Ahmed et al. [4] applied transfer learning on ResNet-18 and ResNet-50 for diagnosing cataract and myopia. Their system achieved impressive accuracy scores (98.9% with ResNet-18), demonstrating that even shallow fine-tuning of pretrained networks can yield high diagnostic performance in medical imaging tasks.

Qin et al. [5] advanced the field by combining transfer and ensemble learning with CNN architectures like MobileNet and ResNet to detect pathological myopia. With a 99.7% accuracy and 99.5% sensitivity, their approach demonstrated the potency of hybrid deep learning models for intricate visual diagnosis.

Finally, Dai et al. [6] focused specifically on distinguishing high myopia from pathological myopia using a two-branch network with ResNet-18 as the backbone. They employed Binary Cross-Entropy loss for general classification and Triplet Loss to refine differentiation between HM and PM. Despite achieving high accuracy, their model relied on a private dataset, limiting generalizability.

These studies highlight key architectural advancements, dataset dependencies, and performance considerations. However, few have tackled real-world deployment challenges, integrated GUI support, or implemented full system pipelines, gaps this project aims to address.

3. DESIGN AND IMPLEMENTATION

The design of the system is centered on practicality, reliability, and clinical applicability. It was developed using Python 3.8 as the core programming language, selected for its mature ecosystem of deep learning and image processing libraries. The system architecture is modular, comprising distinct components for image handling, preprocessing, classification, user interaction, and data storage.

DenseNet121, a densely connected convolutional neural network, was selected after extensive experimentation with other architectures such as VGG16, GoogleNet, and a custom CNN. DenseNet121 was chosen not only for its superior classification performance but also for its computational efficiency and ability to learn hierarchical visual features through dense connectivity.

For model training and testing, Jupyter Notebook was employed within the Anaconda environment. This setup provided flexibility in code execution, visualization, and iterative debugging. The dataset was split into training and testing subsets, with data augmentation techniques including rotation, horizontal flipping, and brightness adjustment applied to increase dataset diversity and improve model generalization. The model was optimized using the Adam optimizer with a learning rate of 0.001. To prevent overfitting, dropout layers were incorporated alongside the data augmentation strategy, and model performance was evaluated using metrics such as accuracy and F1-score.

The user interface was implemented using Streamlit along with Python's built-in GUI libraries, with an emphasis on simplicity and responsiveness. The interface allows users to upload images, view predictions, and access past results. Behind the interface, the system integrates with a SQLite database, which stores patient details, image metadata, and diagnostic outcomes. This integration ensures traceability and facilitates patient follow-up.

In terms of hardware, the system was designed to run effectively on mid-range computing setups, requiring only an Intel i5 or higher processor and 8GB of RAM. This makes the solution accessible and deployable even in resource-constrained settings such as rural clinics or small diagnostic labs. The implementation prioritizes ease of use, speed, and reliability, making it suitable for real-time

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clinical support.

4. SYSTEM ARCHITECTURE

4.1 Dataset

The dataset 'MyopiaDetection' used in this study consists of approximately 2,300 retinal fundus images, categorized into three distinct classes: normal, high myopia (HM), and pathological myopia (PM). Each image is an RGB retinal photograph, preprocessed to a standard resolution of 224×224 pixels to ensure consistency across the dataset. Preprocessing steps included normalization, resizing, and noise removal to enhance image clarity. To improve generalization and avoid overfitting, data augmentation techniques such as image rotation, horizontal flipping, and scaling were applied. The dataset was divided into training and testing subsets for model evaluation, though the exact class distribution was kept approximately balanced.

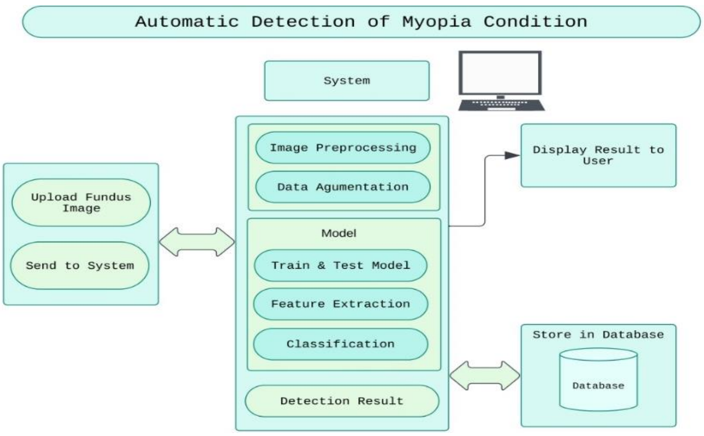

Figure No. 2: Architecture

4.2 Model Configuration and Evaluation

To determine the most effective deep learning model for classifying fundus images, four architectures were implemented and compared: a custom CNN, VGG16, GoogleNet, and DenseNet121. Each model was tested with different activation functions (such as ReLU, ELU, and Leaky ReLU) and dropout rates.

Algorithm	Activation Function	Drop Out	Learning Rate	Accuracy	F1 Score
DenseNet121	Relu	0.5	0.001	94	92
VGG16	ELU	0.3	0.001	92.42	89.31
GoogleNet	ELU	0.4	0.001	93	92
Convolutional Neural Network(CNN)	Leaky Relu	0.4	0.0001	91	91.11

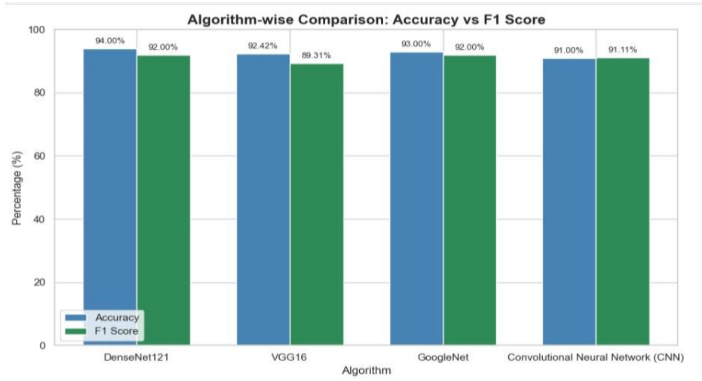

Figure No. 3: Algorithm Classification

After experimentation, DenseNet121 emerged as the top-performing model, achieving an accuracy of 94% and an F1-score of 92%. These metrics indicated strong classification capability across all three classes, with balanced precision and recall.

DenseNet121's performance is a result of its densely connected convolutional layers, which enhance gradient flow and feature reuse. ReLU activation and a learning rate of 0.001 were also used to refine this design. The model's generalization performance was further improved by dropout regularization, which was set at 0.5.

5. RESULTS

Four deep learning architectures were evaluated on the fundus image dataset containing Normal, High Myopia (HM), and Pathological Myopia (PM) classes. DenseNet121 achieved the highest classification accuracy of 94% with an F1-score of 92%. While VGG16, GoogleNet, and the custom CNN also demonstrated reasonable performance, they all fell short of DenseNet121's superior results.

DenseNet121's dense connectivity architecture enabled superior feature extraction of critical retinal characteristics including vessel patterns, optic disc structures, and retinal curvature. The model demonstrated particular effectiveness in distinguishing between High Myopia and Pathological Myopia cases, where visual features often overlap. VGG16 and GoogleNet showed limitations in identifying subtle pathological changes, while the custom CNN lacked sufficient depth for complex feature discrimination.

Robustness testing confirmed DenseNet121's stability across augmented and distorted images, maintaining consistent performance under varying input conditions. The deployed system achieved real-time classification with prediction times of 2-3 seconds per image. The integrated SQLite database successfully recorded all predictions with associated metadata, meeting clinical workflow requirements for practical diagnostic applications.

6. FUTURE WORK

Dataset expansion through diverse imaging devices, ethnic populations, and clinical conditions would enhance model generalizability. Improved differentiation between High Myopia and Pathological Myopia could be achieved using domain-specific attention mechanisms or fine-grained classification layers to capture subtle retinal structural differences.

System enhancements include role-based access control, result explanation features, multi-language support, and longitudinal analysis capabilities for myopia progression monitoring in pediatric and high-risk populations. Model explainability through Grad-CAM or saliency mapping would increase clinician trust by visualizing influential retinal regions in classification decisions.

Deployment on cloud-based platforms or portable diagnostic devices would extend accessibility to rural and semi-urban healthcare facilities, supporting large-scale screening initiatives in underserved populations.

7. CONCLUSION

This research presents the design, development, and evaluation of an automated system for the detection of High Myopia and Pathological Myopia using retinal fundus images. With myopia becoming increasingly prevalent, especially among younger populations, the need for early, accurate, and scalable diagnostic solutions is critical. The system proposed in this study leverages deep learning, specifically the DenseNet121 architecture, to effectively classify fundus images into three clinically relevant categories: Normal, High Myopia, and Pathological Myopia.

Extensive experimentation with various architectures and hyperparameters revealed that DenseNet121 provided superior performance, achieving 94% classification accuracy and an F1-score of 92%. The system's design includes robust preprocessing and data augmentation modules, a responsive Streamlit GUI, and a secure local database for data management. The overall pipeline is modular, efficient, and suited for deployment in clinical settings.

By automating a traditionally manual and time-consuming process, this system aids ophthalmologists in early diagnosis, reduces diagnostic errors, and enhances the accessibility of eye care, particularly in regions with limited specialist availability. With further refinements and clinical validation, the system holds potential for broader adoption in real-world healthcare environments and could play a vital role in combating the rising burden of myopia-related visual impairment.

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