



Detection of Pathological Myopia using Deep Learning Techniques

Anusha¹, Anusha Sadashiva Lokeshwar², Arpita Sanyal³, Deekshitha⁴, Rejeesh Rayaroth⁵

Student, Computer Science and Engineering, MITE Moodabidri, Moodabidri, India¹⁻⁴

Assistant Professor, Computer Science and Engineering, MITE Moodabidri, Moodabidri, India⁵

Abstract: Myopia commonly known as near sightedness, is a prevalent vision problem affecting a considerable portion of the global population, particularly among adolescents and young adults. Detecting myopia early is crucial to effectively manage and prevent associated complications such as retinal detachment, myopic macular degeneration, and glaucoma. While traditional methods of myopia detection often rely on subjective evaluations by eye care professionals, which can be time-consuming and require specialized equipment, our study proposes a novel approach using deep learning techniques. By harnessing advancements in computer vision and deep learning, we have developed a convolutional neural network (CNN) model trained on a large dataset of retinal images. This model is capable of automatically identifying signs of myopia, including optic disc anomalies, retinal stretching, and other characteristic features associated with myopic progression. Our experimental findings demonstrate the effectiveness of this deep learning model in accurately detecting myopia from retinal images with high sensitivity and specificity. Furthermore, the model's performance surpasses that of traditional methods, offering a more efficient and objective approach to myopia detection. This system we have developed shows promise for early screening initiatives, telemedicine applications, and assisting healthcare professionals in the timely diagnosis and management of myopia-related conditions.

Keywords: Myopia detection, Deep learning, Convolutional neural networks, Retinal imaging, Healthcare AI.

I. INTRODUCTION

Pathologic myopia, also referred to as high myopia or degenerative myopia, is a serious condition identified by extensive structural changes in the eye, predominantly impacting the retina and choroid. These changes often lead to distortions in the eye's fundus, significantly affecting vision and giving rise to various complications. Key characteristic of pathologic myopia is its progressive nature, marked by rapid vision changes. Consequently, individuals afflicted by this condition frequently require frequent updates to their corrective lenses, like eyeglasses or contact lenses, typically every four to six months. In the United States, pathologic myopia is recognized as the seventh leading reason for blindness among adults, underscoring the severity of the condition and its potential to cause substantial visual impairment if not untreated or unmanaged. While it affects a relatively small percentage of the population, around 2% of all cases of myopia, it remains a significant concern for health experts.

Certain regions, notably in East Asia such as Singapore, Hong Kong, and Taiwan, exhibit a higher occurrence of pathologic myopia. Environmental factors and genetic predispositions in these areas may contribute to its increased prevalence, highlighting the importance of early detection and intervention. This disability affects quality of life as well as efficiency, and it may have an influence on independence, social interactions, and emotional stability. Moreover, pathologic myopia increases the risk of developing serious complications such as retinal detachment, macular degeneration, and glaucoma, which can result in irreversible vision loss if not managed promptly. These complications stress the significance of regular monitoring and suitable management strategies. In conclusion, pathologic myopia is a substantial public health concern globally, presenting significant challenges concerning visual impairment and associated complications. Addressing this condition necessitates comprehensive approaches focused on early detection, regular monitoring, and tailored interventions to preserve vision and enhance the affected individuals' quality of life.

II. RELATED WORK

Their study, "Automated Diagnosis of Pathological Myopia from Heterogeneous Biomedical Data," was published [3]. They suggested using PM-BMII, a computer-aided diagnosis technique, to identify pathological myopia. Based on various combinations of data sources, such as retinal fundus image data, clinical data, and gene-related data, it automatically detected problematic myopia. Their results showed an 88% Area under the Curve (AUC) when they combined many possibilities.



However, using retinal image processing and the deep learning method Convolutional Neural Network [3], it is possible to diagnose pathological and non-pathological myopia with greater accuracy.

The "Relation Networks for Optic Disc and Fovea Localization in Retinal Images" study by Sudharshan et al. [7] introduced a novel technique for optic disc and fovea detection. They concentrated on the issue in their approach of locating the Fovea and Optic disc centres. Through parallel processing and modeling of their respective figures and presence, their method is able to pinpoint the centres of the Fovea and the Optic disc. These methods provide the fovea and optical disc's centre location. However, the entire optical disk segmentation was necessary for lesion diagnosis.

III. METHODOLOGY

3.1. Data Collection and Preprocessing in Myopia Detection : In the realm of myopia detection and classification with deep learning, data is usually gathered from hospitals, clinics, research institutions, and publicly accessible datasets. These sources provide a plethora of medical images, including retinal images and OCT scans. Retinal images reveal structural alterations such as posterior staphyloma, whereas OCT scans offer detailed cross-sectional viewpoints helpful in recognizing thinning or fluid accumulation. Public datasets complement these sources, enriching the data pool for robust model training.

3.2 Feature Extraction : We use a Convolutional Neural Network (CNN) model to identify salient features in fundus pictures and predict the probability of pathological myopia based on eyeball size. Three convolutional layers and three max pooling layers make up this CNN architecture, which is intended to effectively extract features from images. By applying this model to fundus photos, we are able to extract detailed and useful characteristics that take into consideration differences in lighting, scale, and other image-related aspects. With the use of these extracted features, the model is able to identify pertinent patterns and characteristics in the photos, which in turn helps identify the nerves, retina, and lens of the eye accurately. It also helps determine the size of the eyeball, which helps determine the likelihood of pathological myopia.

3.3 Model development and training : Obtaining a broad dataset of labeled pictures for training, validation, and testing is the first step in developing and training a CNN model. Create the model architecture by deciding on the number of layers, the kinds of layers (such as pooling and convolutional), and the filters, filter sizes, and activation functions that are used in each configuration . Consider employing techniques like batch normalization and dropout for improved generality.. To increase diversity and generalization, add more features to the training set by applying operations like rotation, flipping, scaling, and translation. Provide the optimizer, evaluation metrics, and loss function when assembling the model. Utilizing backpropagation and optimization techniques, train the model on the training set of data, keeping an eye on its performance on the validation set to avoid overfitting. Adjust hyperparameters in light of validation results. Utilizing the test set, assess the trained model.

3.4 Model evaluation and prediction : There are multiple processes involved in the evaluation and prediction process after a CNN model has been developed and trained. Initially, the test dataset is used to evaluate the trained model in terms of performance measures like accuracy, precision, recall, and F1-score. This assessment aids in determining how effectively the model extrapolates to unknown data. The trained model predicts the class labels or probabilities for each class given new, unseen images. Based on the model's outputs, these predictions can be further examined to help with decision-making or action planning. Analyzing the model's predictions—both accurate and inaccurate classifications—is crucial to spot any trends or potential areas for development. This study can direct data or inform model updates in the future.

IV. PROPOSED SYSTEM

Data gathering: Compile a collection of retinal pictures from patients, comprising both myopic and healthy eyes. Make sure the dataset reflects a variety of populations and is varied.

Data preprocessing: To improve quality and reduce noise, preprocess the retinal pictures. The photos can be standardized by using methods including contrast modification, scaling, and normalization.

Design of Model Architecture: Convolutional Neural Network (CNN): Create an architecture for a CNN that may utilize retinal pictures to extract features pertinent to the identification of myopia. Adjust the pre-trained models using the myopia dataset to make them more suitable for the particular job of detecting myopia.



Model Training: Utilizing suitable optimization algorithms and loss functions (e.g., binary cross-entropy for binary classification), train the CNN model on the supplemented dataset. To avoid overfitting, keep an eye on the model's performance on a validation set and use strategies like early halting.

Prediction: Utilize the trained model to distinguish between myopic and normal retinal pictures. Probability scores that represent the classification's degree of confidence can be appended to the model's predictions.

Integration and Deployment: Construct an application that is easy to use by integrating the learned model.

V. RESULTS

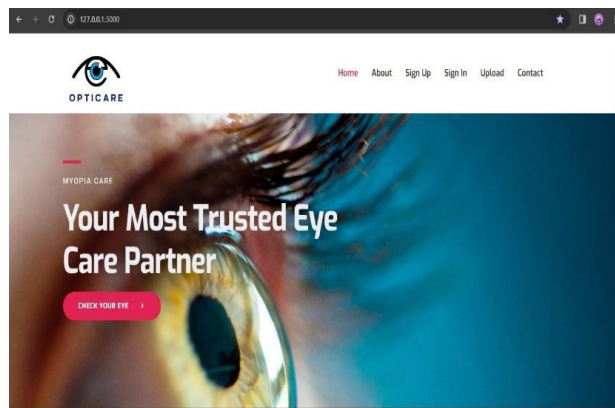


Figure 5.1 Home Page

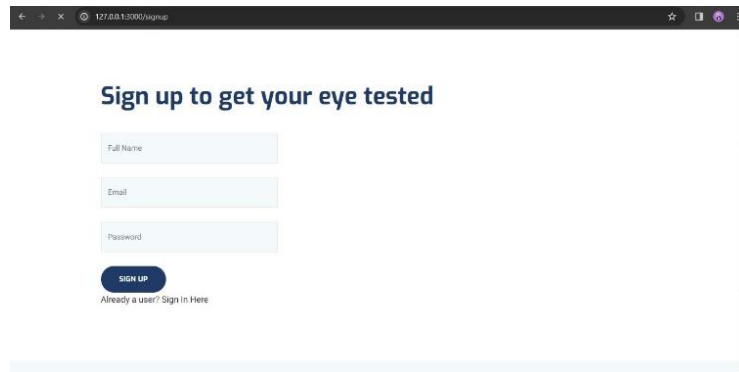


Figure 5.2 Page to Sign Up

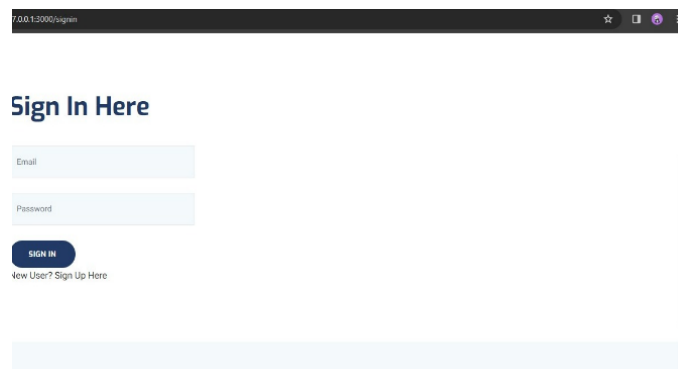


Figure 5.3 Page to Sign-In

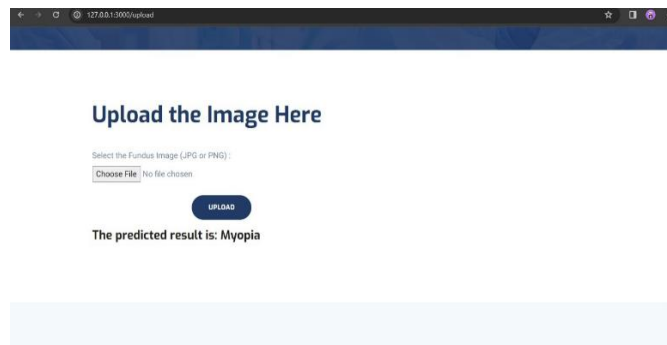


Figure 5.4. Page to detect Pathological Myopia

VI. FUTURE WORK

Dataset Expansion: To guarantee the generalizability of the model, gather a variety of datasets with annotations from different demographics and ethnicities.

Fine-Grained Classification: Develop models that can distinguish between various forms and degrees of pathological myopia, which will help with accurate diagnosis and treatment planning.

Multi-modal fusion: Boost detection and classification accuracy by merging data from several imaging modalities.

Weakly Supervised Learning: Investigate techniques that use unlabeled data for training in order to reduce the amount of manual annotation required.

REFERENCES

- [1] Elango, Sivasankar, Maiya, Shishira, and Chandra Babu, Sudharshan. 2018. Relation Networks for Localization of Fovea and Optic Disc in Retinal Images
- [2] Holden, B. A. et al. Global prevalence of myopia and high myopia and temporal trends from 2000 through 2050. *Am. Acad. Ophthalmol.* 123(5), 1036–1042 (2016).
- [3] Sunday, M., & Lauer, A. K. Pathologic myopia (myopic degeneration). *American Academy of Ophthalmology, EyeWiki.* (2015).
- [4] Holden, B. A. et al. Global prevalence of myopia and high myopia and temporal trends from 2000 through 2050. *Am. Acad. Ophthalmol.* 123(5), 1036–1042 (2016).
- [5] Using fundus images, Freire, C.R., da Costa Moura, J.C., da Silva Barros, D.M., and de Medeiros Valentim, R.A. "classified pathological myopia using automatic lesion segmentation 2020."