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DEEP LEARNING TECHNIQUES FOR DETECTION OF MYOPIC DISORDERS

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Abstract : The prevalence of myopia, a common refractive error causing blurred distant vision, has been steadily increasing. In more severe cases, myopia manifests as high myopia and pathological myopia, which can lead to irreversible vision impairment due to associated complications like retinal detachment and macular degeneration. High myopia and pathological myopia pose serious threats to visual health, necessitating accurate and early detection for effective intervention. This research focuses on leveraging Convolutional Neural Networks (CNNs) for the automated detection and classification of high myopia and pathological myopia from fundus images. CNNs have proven to be powerful tools in image analysis tasks, particularly in discerning intricate patterns and features. Fundus photographs and optical coherence tomography scans are employed to capture detailed anatomical structures associated with high myopia and pathological myopia.

***IndexTerms* - Myopia, Nearsightedness, Myopic vision, Vision problems, CNN image detection.**

I. Introduction

Myopia typically manifests with symptoms such as blurred distance vision, squinting, eyestrain, and headaches when trying to see distant objects. Children and teenagers often experience progressive myopia, where their vision worsens over time. Myopia can be influenced by both genetic and environmental factors. Individuals with a family history of myopia are at a higher risk. Additionally, spending significant time on activities that involve close-up work, such as reading or using digital screens, can contribute to myopia development. Myopia is a global concern, and its prevalence is increasing. It is particularly common in East Asian countries, where rates of myopia are notably high among school-age children. Early detection of myopia is crucial for managing the condition effectively. If left untreated, myopia can lead to more severe eye problems, such as cataracts, glaucoma, retinal detachment, and myopic macular degeneration, which can potentially result in vision loss.

II. LITERATURE REVIEW

Cheng Wan , Han Li , Guo-Fan Cao, Qi Jiang and Wei–Hua Yang in the year 2021 proposed a computer aided algorithm using Deep Convolutional Neural Networks to detect the risk of high myopia. The fundus images in the paper[1] acquired were classified into 3 categories i.e. normal fundus were labeled as 0, low risk high myopia were labeled as 1 and high risk high myopia was labeled as 2. This project involved human experts of the particular field to check the accuracy of their algorithm. This experimental result shows that out of 26 normal fundus images the result of DCNNs were all correct whereas the human expert only correctly classified 23 images and wrongly classified three images as low-risk high myopia.

Ruben Hemelings, Bart Elene, Matthew B. Blaschkoc, Julie Jacob, Ingeborg Stalmans, Patrick De Boever in the year 2019 investigated reports on the results of deep learning models developed for the recently introduced Pathological Myopia (PALM) dataset, which consists of 1200 images. This paper [2] has evaluation metrics include area under the receiver operating characteristic curve (AUC) for PM detection, Euclidean distance for fovea localization, and Dice and F1 metrics for the semantic segmentation tasks (optic disc, retinal atrophy and retinal detachment). They also introduce a new Optic Nerve Head (ONH)-based prediction enhancement for the segmentation of atrophy and fovea. They successfully classified pathological myopia and segmentation of associated lesions achieving an AUC of 0.9867 for PM detection, and a Euclidean distance of 58.27 pixels on the fovea localization task, evaluated on a test set of 400 images. Dice and F1 metrics for semantic segmentation of lesions scored 0.9303 and 0.9869 on optic disc, 0.8001 and 0.9135 on retinal atrophy, and 0.8073 and 0.7059 on retinal detachment.

Ruitao Xie , Libo Liu , Jingxin Liu , Connor S Qiu in the year 2019 presented a summary of transfer learning based methods for several fundus images of myopia which are difficult to detect. This paper[3] include tasks like classification of pathological and non-pathological myopia, localisation of fovea, and segmentation of optic disc. They have developed several deep learning based pathological myopia fundus image analysis applications with pre-trained VGG and ResNet, which can quickly develop several modified models for different tasks, and achieve impressive performance with a small amount of training data.

Zhuo Zhang, Yanwu Xu , Jiang Liu, Damon Wing , Kee Wong in the year 2013 proposed a computer-aided diagnosis framework for Pathological Myopia diagnosis through Biomedical and Image Informatics(PM-BMII) in the paper[4]. Through the use of multiple kernel learning (MKL) methods, PM-BMII intelligently fuses heterogeneous biomedical information to improve the accuracy of disease diagnosis. Data from 2,258 subjects of a population-based study, in which demographic and clinical information, retinal fundus imaging data and genotyping data were collected, are used to evaluate the proposed framework. The experimental results show that PM-BMII achieves an AUC of 0.888, outperforming the detection results from the use of demographic and clinical information 0.607, genotyping data 0.774 or imaging data 0.852 alone. The accuracy of the results obtained demonstrates the feasibility of using heterogeneous data for improved disease diagnosis through the proposed PM-BMII framework.

Jiang Liu, Damon W.K. Wong, Joo Hwee Lim, Ngan Meng Tan, Zhuo Zhang, Huiqi Li, Fengshou Yin, Benghai Lee, Seang Mei Saw, Louis Tong, Tien Yin Wong in the year 2010 developed a system known as PAMELA (Pathological Myopia Detection Through Parapapillary Atrophy) to automatically assess a retinal fundus image for pathological myopia. This paper[5] focuses on the texture analysis component of PAMELA which uses texture features, clinical image context and support vector machine-based classification to detect the presence of pathological myopia in a retinal fundus image. The results shows and accuracy of 87.5% and a sensitivity and specificity of 0.85 and 0.90 respectively.

Ananth Kalyanasundaram, Surya Prabhakaran, J. Briskilal and D. Senthil Kumar in the year 2020 the paper revealed that myopia is an extreme case of nearsightedness which affects individuals during their most productive years, leads to vision loss which is progressive and irresistible. The dataset was downloaded from the Pathological Myopia (PALM) challenge as a part of the IEEE International Symposium of Biomedical Imaging 2019 conference. This paper[6] proposed to apply the DenseNet architecture on the PALM dataset. We also conducted a survey on the performance of previous architectures. The proposed model was then compared with the performance of other stateof-the-art architectures. We used data augmentation techniques to expand the dataset. For training they used 320 images and validated the model on 80 images. These images were then trained on the DenseNet architecture using the cross-entropy loss function for 100 epochs. The best model was tested on 400 unseen fundus images and achieved an accuracy of 98.08%.

Li Lu, Peifang Ren, Xuyuan Tang, Ming Yang, Minjie Yuan , Wangshu Yu, Jiani Huang , Enliang Zhou, Lixian Lu, Qin He, Miaomiao Zhu, Genjie Ke and Wei Han in the year 2021 developed a series of deep learning algorithms and artificial intelligence (AI)–models for automatic PM identification, MM classification, and “Plus” lesion detection based on retinal fundus images in the paper[7]. A total dataset of 32,010 color retinal fundus images was manually graded for training and cross-validation according to the META-PM classification and also 1,000 images from 732 patients from the three other hospitals in Zhejiang Province, serving as the external validation dataset. The area under the receiver operating characteristic curve (AUC), sensitivity, specificity, accuracy, and quadratic-weighted kappa score were calculated to evaluate the classification algorithms. The precision, recall, and F1-score were calculated to evaluate the object detection algorithms. In five-fold cross-validation, algorithm I achieved robust performance, with accuracy = 97.36%, AUC = 0.995, sensitivity = 93.92% and specificity = 98.19% . The macro-AUC, accuracy, and quadratic-weighted kappa were 0.979, 96.74% and 0.988 for algorithm II.

Jun Li, Lilong Wang, Yan Gao, Qianqian Liang in the year 2022 aimed to build a model for automated detection of MM from retinal fundus images using DCNN models in the paper[8]. A dual-stream DCNN (DCNN-DS) model that perceives features from both original images and corresponding processed images by color histogram distribution optimization method was designed for classification of no MM, tessellated fundus (TF), and pathologic myopia (PM). A total of 36,515 gradable images from four hospitals were used for DCNN model development, and 14,986 gradable images from the other two hospitals for external testing. The proposed model demonstrated reliable performance with high sensitivity, specificity and AUC to classify different MM levels fundus photograph source from clinics and an help identify MM automatically among the other large myopic groups.

Ruonan Wang , Jiangnan He, Qiuying Chen, Luyao Ye, Dandan Sun, Lili Yin, Hao Zhou, Lijun Zhao, Jianfeng Zhu, Haidong Zou, Qichao Tan, Difeng Huang, Bo Liang, Lin He, Weijun Wang, Ying Fan, Xun Xu in the year 2023 developed an algorithm to quickly classify pathologic myopia based on colour fundus photographs in the paper[9]. This study included 10,347 fundus images of these, 8210 were used for training and validation and 2137 were used for testing. The algorithm was trained, validated, and externally tested to screen myopic maculopathy which consists of 4 categories: normal or mild tessellated fundus, severe tessellated fundus, early –stage PM and advanced-stage PM. In the validation data set, the model detected normal or mild tessellated fundus, severe tessellated fundus, early-stage PM, and advanced-stage PM with AUCs of 0.98, 0.95, 0.99, and 1.00, respectively; while in the testing data set the model had AUCs of 0.99, 0.96, 0.98, and 1.00.

Zhengjin Shi, Tianyu Wang, Zheng Huang, Feng Xie, Guoli Song in the year 2020 presented a MDNet to automatically detect myopia in Optos fundus images. The Optos fundus images used in the paper produces 3 kinds of fundus images for patient: pseudocolour fundus images, green laser images and red laser images. First an automatic optic disc recognition is applied to extract the ROI and remove noise, then data augmentation method is applied to reduce overfitting. An MDNet composed of Attention dense blocks is constructed to detect myopia in Optos fundus images. This paper[10] presents a MDNet that can make full use of shallow features to minimize information loss and emphasize the significant feature channels.

Tien-En Tan, Ayesha Anees, cheng Chen, Shaohua Li, Xinxing Xu, Zhe Xiao, Marcus Ang in the year 2021 developed and tested retinal photograph based learning algorithms for detection of myopic macular degeneration and high myopia. The paper[11] uses a total 2,26,686 retinal images. They also compared the performance of deep learning algorithms against six human experts in the grading of a randomly selected of 400 images from external datasets and also used a block-chain based AI platform to demonstrate real world applications of data transfer, model transfer and model testing. They showed diagnostic performance with AUC of 0.969 and outperformed six expert graders with an AUC of 0.973.

Beng-Hai Lee, Damon Wing Kee Wong, Zhou Zhang, Joo Hwee Lim, Jiang Liu have described in the paper[12] two modules in the PAMELA system based on texture analysis and gray level analysis. A decision engine is then used to fuse the two individual results to obtain an overall analysis. From the results run on a sample batch of images from the Singapore Eye Research Institute, a sensitivity of 0.9 and a specificity of 0.94 with a total accuracy of up to 92.5% is obtained.

Ujjwal Baid, Bhakti Baheti, Prasad Dutande and Sanjay Talbar in the year 2019 have developed a Convolutional Neural Network (CNN) based system to estimate probability/risk of the patient to be diagnosed with PM from his retinal images and have also segmented optic disc from the retinal images with novel Residual UNet architecture in the paper[13]. Validation data results are evaluated from the online server and achieved 0.9973 and 0.901 for the task of PM classification and optic disc segmentation.

Sallam Osman Fageeri , Shyma Mogtaba Mohammed Ahmed, Sahar Abdalla Almubarak, Abubakar Aminu Muazu in the year 2017 presented in this paper intelligent machine learning algorithms are used to classify the type of an eye disease based on ophthalmology data collected from patients of Mecca hospital in Sudan in the paper[14]. Three machine-learning techniques are used to predict the severity of the eye that occurred during the investigation, which are Naïve Bayesian, SVM, and J48 decision tree.

G. Shobana, Dr. S. Nikkath Bushra in the year 2020 presented in this paper, myopic data set which is classified using various supervised machine learning techniques like logistic regression, decision tree, support vector machine, Naïve Bayes, K-nearest neighbor, random forest and neural network and the best model is determined. Multi-layer perceptron achieved highest accuracy among all the machine learning models. The proposed methodology in the paper[15] optimizes the prediction accuracy further by selecting important features through recursive feature elimination with tree-based classifier.

Namra Rauf, Syed Omer Gilani & Asim Waris in the year 2021 aimed at developing an algorithm for automatic detection of pathological myopia based on fundus images in the paper[16]. A deep learning technique of convolutional neural network (CNN) is developed in Spyder. The fundus images are first preprocessed. The preprocessed images are then fed to the designed CNN model. The CNN model automatically extracts the features from the input images and classifies the images i.e., normal image or pathological myopia. The best performing CNN model achieved an AUC score of 0.9845. The best validation loss obtained is 0.1457.

Jaydeep Devda, R. Eswari in the year 2019 developed a system through deep learning method with Convolutional Neural Networks (CNN) is used for classification and U-net model is used for Image segmentation which shows that it achieves highly competitive result. This paper[17] focuses on the problems of classification of Pathological myopia images and nonpathological myopia images and optical disc, fovea detection, localization, lesions (atrophy and detachment) segmentation with 400 samples provided by International Symposium on Biomedical Imaging (ISBI).

Siying Dai, Leiting Chen, Ting Lei, Chuan Zhou ,Yang Wen in the year 2020 developed deep learning algorithm was trained validates and externally tested to screen myopic maculopathy which was classified into four categories normal or mild tessellated fundus, severe tessellated fundus early stage PM , and advanced stage PM in the paper[18]. In the validation data set the model detected normal or mild tessellated fundus severe tesselatted fundus, early-stage PM and advanced stage PM with AUCs of 0.98, 0.95.

Ran Du, MD, Shiqi Xie, MD in the year 2021 determine whether eyes with pathological myopia can be identified and whether each type of myopic maculopathy lesion on fundus photographs can be diagnosed by deep learning algorithm in the paper[19]. Dataset is collected from advanced clinical centre for myopia of the Tokyo medical and dental university. The novel DL models and system achieved high sensitivity and specificity in identifying the different types of lesion of myopic maculopathy. This result will assist in the screening for pathological myopia.

Maryam Badar, Muhammad Haris in the year 2020 did an analysis to hold imperative position for the identification and classification of retinal disease such as diabetic retinopathy in the paper[20]. The input was given is retina image. Retinal image analysis through DNNs is a nascent field. Although research has been conducted in extraction of retinal land marks and pathologic but the epitome of this technique is yet to be witnessed.

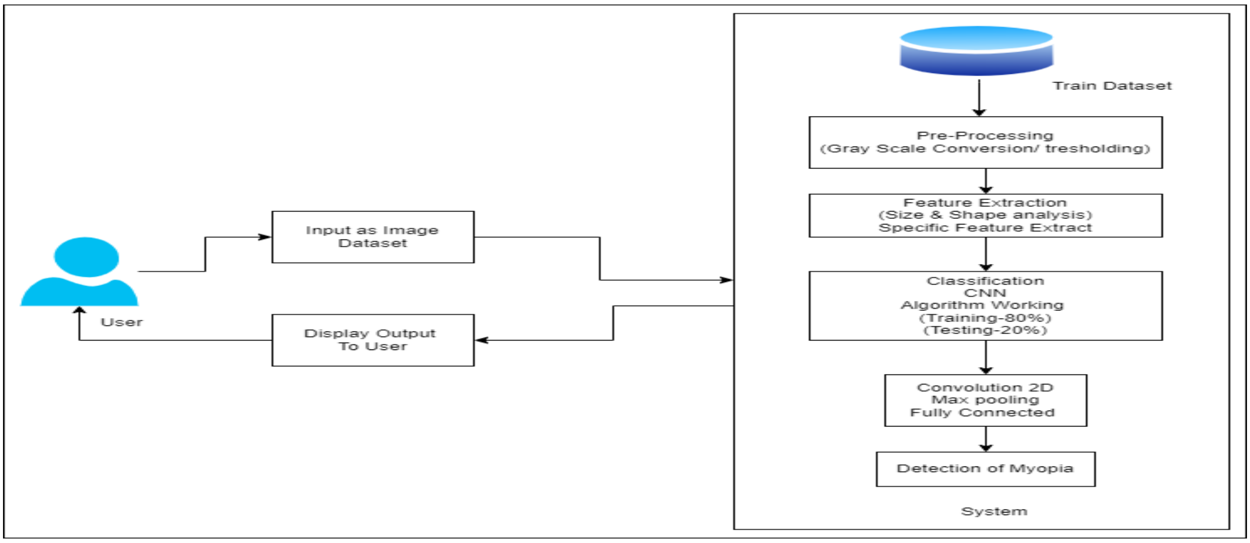
III. RESEARCH GAP

The existing system for classifying myopia is based on the refractive error and the axial length of the eye, which are measured by objective methods such as auto-refraction and biometry. The existing system is based on refractive error and axial length, which do not capture the dynamic nature of myopia development and progression. The existing system's parameters may not be sufficient or accurate to predict the risk of myopia-related complications. This project uses Deep Learning techniques to understand the ocular and non-ocular features of children such as age, gender, parental myopia, reading habits, screen time, lens thickness, corneal curvature, anterior chamber depth etc. This project is based on dynamic features that reflect the biological processes underlying myopia development and progression. This project is expected to provide more accurate and personalized prediction of myopia which can help in better prevention and treatment strategies for myopia in children.

IV. PROPOSED METHODOLOGY

Initially, the fundus images gathered from various Hospitals are added to the dataset. Fundus images are the images of the retina of the eye with a fundus camera. The data pre-processing is the next step to understand the images and its severe areas properly in this step we had used data pre-processing techniques such as Gray-Scale Method and Thresholding. Gray-Scale method converts the red, green and blue color channels in shades of gray color. Thresholding is to convert a gray-scale image into a binary image, where pixels are classified as either foreground (object) or background.

The next step is the Feature Extraction here we are reducing the size and shape of images to understand the image and also for the clarity of the images. After feature extraction, the model training is done using the deep learning algorithm Convolutional Neural Network (CNN) which is used for image processing. For training the model using CNN algorithm, the hidden layer consist of 3 main components such as Convolution 2D layer, Max pooling layer, Fully connected layer. Afterwards, it will detect whether the image is Myopic or Normal if it is Myopic then whether it is High Myopia or Pathological Myopia.



System Architecture

Data Collection: Gather a dataset of fundus images, ensuring representation of various severity levels and clinical manifestations. Fundus images are the images of the retina of the eye with a fundus camera. Fundus images and photography is important for diagnosing and treating various posterior segments and other ocular diseases. Fundus photography captures the images of the retina, optic nerve head, macula, retinal blood vessels, choroid, and the vitreous. Fundus photography impacts the detection and screening of various causes of treatable and preventable blindness, notably diabetic retinopathy, age-related macular degeneration, glaucoma, and retinopathy of prematurity. These fundus images contains Pathological Myopia, High Myopia and Normal eye images.

Data Pre-processing : The dataset contains the images in RGB format i.e. Red, Green and Blue color format. So as to understand the images and its severe areas properly in this step we had used data pre-processing techniques such as Gray-Scale Method and Thresholding.

Gray-scale: Converting an image to grayscale involves removing the color information and representing each pixel using only its intensity value. The most common method for grayscale conversion is to take a weighted average of the red, green, and blue color channels in a color image. In this step, the image gets converted into different shades of gray The darker part of the image show the affected part of the image, such as choroidal thinning or areas of atrophy. The steps for gray scaling the fundus images are: Import the fundus images into your image processing environment. These images are usually in color, with three channels (red, green, and blue). Convert the color fundus images to grayscale. This can be done using the following formula: Gray = 0.299 × Red + 0.587 × Green + 0.114 × Blue. Apply this formula to each pixel in the image to calculate the corresponding grayscale value.

Thresholding: The basic idea behind thresholding is to convert a grayscale image into a binary image, where pixels are classified as either foreground (object) or background. The steps for thresholding is given as: Choose an appropriate threshold value. This can be done through automated methods, such as Otsu's method, which calculates an optimal threshold based on the image histogram. Apply a binary threshold to the grayscale image. Pixels with intensity values above the threshold are set to one (foreground), while those below the threshold are set to zero (background). In cases where the illumination varies across the image, we used adaptive thresholding techniques. Adaptive thresholding adjusts the threshold locally based on the pixel neighborhood, making it more robust to variations in lighting conditions. Depending on the characteristics of the images and the desired outcome, you may apply post-processing steps to refine the binary mask. This can include morphological operations (e.g., erosion, dilation) to remove noise or connect nearby regions. Visualize the binary mask to inspect the segmented regions. This step ensures that relevant structures or abnormalities associated with myopia are appropriately highlighted.

Feature Extraction : Extracting features such as size, shape and its dimension. The size analysis can be done to identify and label different regions of the image by using connected component analysis, measuring the size of the connected component corresponding to the optic disc, mainly the larger optic disc may be more prone to be myopic, measuring the size of the connected component corresponding to macula, changes in macular size may be relevant in myopic conditions and also measuring the size of the lesions. For shape analysis extracting contours of the identified regions like optic disc, macula, lesions and analyze their shapes.

Model training : Choosing a suitable deep learning architecture, such as a Convolutional Neural Network (CNN), considering the complexity of pathological myopia and high myopia features.

CNN: CNNs are particularly effective in handling spatial hierarchies and local patterns in data, making them well-suited for tasks where the arrangement of features is crucial, such as image recognition. In CNN algorithm the 3 most prominent layers are input layer, hidden layers and output layer. The input layer consist of the input provided by the user, the hidden layers consist of various types of layers to train as well as test the model and the output layer consist of the output generated by our system. The mainly used hidden layers in our system is Convolution 2D layer, Max pooling layer, Fully connected layer.

Convolution 2D layer: These layers use convolutional operations to scan the input data with small filters or kernels. These filters learn spatial hierarchies of features, enabling the network to recognize patterns and shapes. CNNs typically consist of multiple convolutional layers stacked together. Each layer captures increasingly complex and abstract features by combining the low-level patterns learned in earlier layers.

Max Pooling layer: The Max Pooling layer plays a crucial role in down-sampling feature maps, reducing spatial dimensions, and enhancing certain aspects of the model's performance. These layers reduce the spatial dimensions of the input volume, decreasing the amount of computation in the network. Max Pooling is typically applied after convolutional layers, contributing to hierarchical feature learning. Features learned in convolutional layers are progressively down-sampled, capturing both local and global information. The use of Max Pooling and its position in the architecture can impact the overall design of the CNN and its ability to learn hierarchical features.

Fully connected layer: These layers connect every neuron in one layer to every neuron in the next layer. After passing through convolutional and pooling layers, the extracted features from different regions of the input images are flattened into a one-dimensional vector. Each neuron in the FC layer is connected to all neurons in the previous layer, capturing complex relationships. During training of the model, the weights of the fully connected layers are adjusted through back-propagation and gradient descent to minimize the loss function, making the model more accurate in classifying pathological myopia and high myopia.

Detection of Myopia: This model will predict if the image provided by the user is myopic image or normal image and if it myopic image then whether it is High Myopia or Pathological Myopia. This model will also give some additional information about the symptoms for the myopic disorder.

V. CONCLUSION

The conclusion reached depends on the findings of these assessments and involve a diagnosis of myopia, an assessment of its severity, and recommendations for corrective measures and on-going eye care. Early detection and management are essential to address myopia effectively and prevent potential complications associated with high myopia.

VI. FUTURE SCOPE

1. The system can be designed not only for the initial diagnosis but also for continuous monitoring of myopic conditions.
2. Integrating the detection system with electronic health records (EHR) and hospital management systems streamlines the diagnostic process.
3. Extending the system to telemedicine platforms allows remote consultations.

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