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A Two-Stage Machine Learning Approach for Enhancing Attention-Deficit/Hyperactivity Disorder Diagnostic Accuracy: Optic Disc Segmentation and Symptom Severity Classification

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ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by pervasive patterns of inattention, hyperactivity, and impulsivity that are inappropriate for a person's developmental level. Individuals with ADHD may have difficulty sustaining attention, following through on tasks, and organizing activities. The traditional diagnosis of ADHD employs various methods, such as Electro Encephalo Graphy (EEG) scans, self-checklists, and computer-aided assessments. However, these methods are often time-consuming and can sometimes lack scientific rigor. EEG scans, while useful for identifying certain brain activity patterns, do not provide definitive evidence for diagnosing ADHD. Self-checklists rely heavily on subjective reporting, which can be influenced by personal biases and inaccuracies. Computer-aided assessments, although helpful in standardizing evaluations, may not fully capture the complexity of ADHD symptoms and their impact on daily functioning. To address this issue, I propose a two-stage machine learning system to accurately screen ADHD symptom severity in a classification manner. The proposed system takes fundus images as input and isolates the optic disc area, which is highly correlated with the severity of ADHD. This isolated optic disc area, along with the full fundus image, is then inputted into the severity classification network. The system outputs the probabilities of four levels of ADHD severity. The proposed system achieved an accuracy of 85.62% on a public dataset.

Introduction

Attention Deficit/hyperactivity disorder, commonly known as the abbreviation ADHD, is a mental disorder that involves lacking focus, disturbance in thinking, mood swings, hyperactivity, and behavioral abnormality. The global prevalence of ADHD is estimated to be around 5% for adolescents and 2.5% for adults (CDC 2024). In the United States of America, ADHD affects children and adolescents aged 5–17 years 11.3% and approximately 4.4% of the adult population. Based on the CDC symptoms of ADHD in children people with ADHD often exhibit symptoms of inattention and hyperactivity-impulsivity. They frequently fail to pay close attention to details or make careless mistakes in schoolwork, work, or other activities, therefore paying attention to tasks or activities can be a significant challenge and they often do not seem to listen when spoken to directly. This lack of focus extends to following through on instructions, resulting in unfinished schoolwork, chores, or duties in the workplace. Organizing tasks and activities is often troublesome, leading to avoidance, dislike, or reluctance to engage in tasks that require sustained mental effort. Additionally, individuals with ADHD are easily distracted and forgetful in daily activities.

Hyperactivity and impulsivity are also prominent characteristics of ADHD. Those affected may often fidget with or tap their hands or feet, or squirm in their seat. They may leave their seat in situations where remaining seated is expected, and often run about or climb inappropriately. Playing or engaging in leisure activities quietly can be difficult, as they are frequently "on the go," acting as if "driven by a motor." Common behaviors include excessive talking, blurting out answers before completing questions, and having trouble waiting their turn. They often interrupt or intrude on others, such as butting into conversations or games. However, while there is reason to suspect ADHD in an individual one must also keep in mind these additional considerations: These symptoms must be present before the age of 12 and should be evident in two or more settings (e.g., at home, school, or work); the symptoms must also interfere with, or reduce the quality of, social, academic, or occupational functioning.

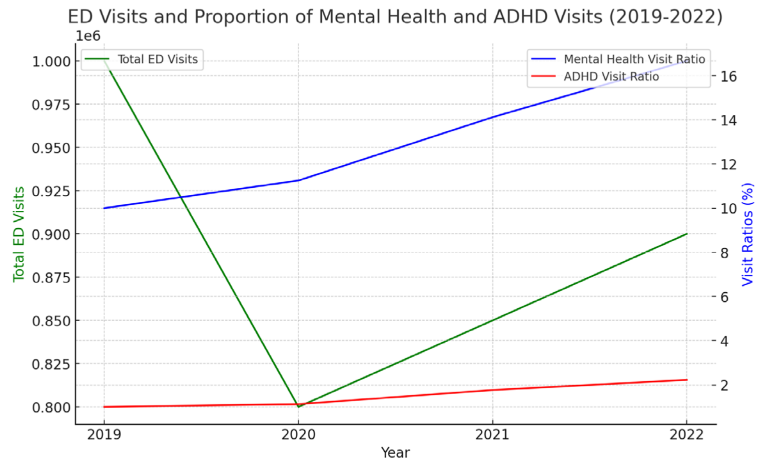


Figure 1. Trends in ED Visits and Proportion of ADHD and Mental Health-Related Visits (Abrams 2022)

There had been a drop in the total ED visits in 2020 due to concerns about the spread of COVID-19. Next, there followed an increase in 2021 and 2022. Visits for mental health concerns have been increasing from 2019 to 2022, with visits specifically for ADHD showing a notable difference starting from 2020. A clinical psychologist based in Virginia Beach, Jeffery S. Katz, PhD stated that people with ADHD rely on structure and that when that structure is removed or altered it has an impact. As in the symptoms that were under control became more impairing.

To solve the aforementioned problem, in this research paper, I proposed a novel ADHD screening system utilizing the optic nerve head area. The proposed system comprises an optic disc segmentation network and an ADHD severity classification network. The optic disc segmentation network processes fundus photographs to generate a segmentation map that isolates the optic disc area. The ADHD severity classification network then uses these isolated optic nerve head areas as input to screen and predict the severity of ADHD based on individual fundus photographs.

Related Work

Fundus Photograph

Fundus photography consists of taking detailed scans of the retinal surface through a fundus photographic camera. It provides a visual description of the microvascular changes within the retina, leading to these abnormalities being detected so that they can be further monitored and dealt with. The fundus images bring numerous changes and benefits to neuroscience in diagnosis and measurements.

(a) (b) (c)

Figure 1. (a): human eye anatomy, (b): fundus camera, and (c): fundus photography

There are various ways of detecting a neurodevelopment disorder or even other neurological disorders, but the changes that the fundus images will bring are quite intriguing. The biggest factor would be convenience. Fundus imaging is non-invasive and relatively quick, making it a practical tool for large-scale screenings or longitudinal studies. A camera shown in the image (b) will be used to capture the images of our eye shown in the image (a). The result would be in the form of image (c) which gives us a clear visual of the optic disc and the optic nerves. This makes it easier to detect even the slightest changes in the nervous system.

In this research, I proposed a machine learning-based approach for screening ADHD using fundus photography. A detailed explanation of the proposed ADHD screening system will be elaborated in Chapter 3.

Image Classification

Image classification is simply a product where a computer algorithm is trained to categorize its input into categories or classes, thereby producing its output. The input is most likely an image that is being requested to be put into a certain category and the output usually is the category/class/label for said input.

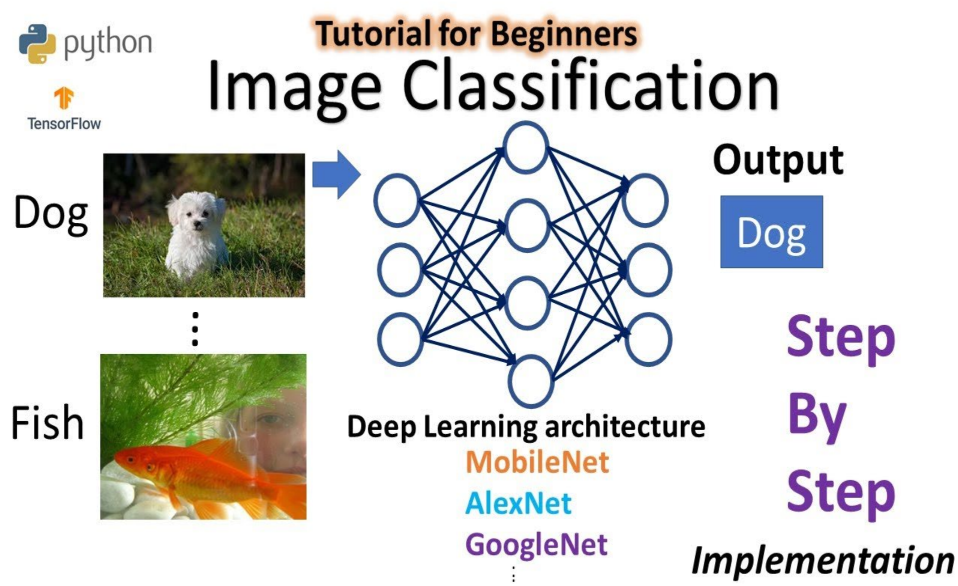


Figure 2. Explanation of image classification (DeepLearning by PhDScholar 2020)

Convolutional Neural Networks (CNNs) are often used to develop image classification systems due to their remarkable performance in many computer vision tasks. They are also widely utilized for medical image analysis.

Convolutional layers, the core components of these networks, apply a set of filters (also known as kernels) to the input image. Each filter slides over the image, performing a convolution operation to produce a feature map. This process helps detect various features such as edges, textures, and patterns at different spatial locations in the image. The filters in the initial layers usually detect low-level features, while deeper layers capture more complex patterns and high-level features.

In this research, I developed an ADHD severity classification network utilizing a convolutional neural network. A detailed explanation of the proposed approach is provided in Chapter 3.

Proposed Methodology

The proposed method is used to address and correct the issues with the traditional ADHD diagnosis methods. This method consists of two components: the Optic Disc Segmentation Network and the ADHD Severity Prediction Network.

Optic Disc Segmentation Network

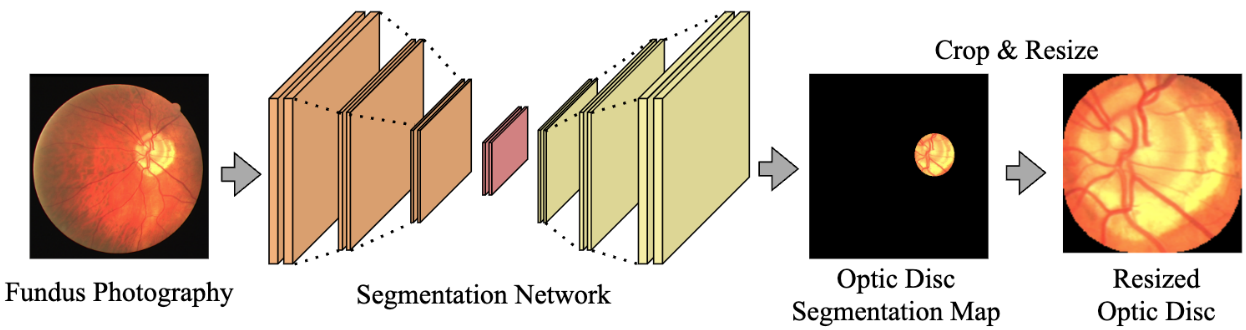


Figure 3. Architecture of the proposed optic disc segmentation network

Equation 1: Binary Cross Entropy Loss Function

$$L_{seg} = -\sum_{x}\sum_{y} gt(x,y) \times log_e\big(S(x,y)\big) + (1 - gt(x,y)) \times log_e\big(1 - S(x,y)\big)$$

The Optic Disc Segmentation Network is responsible for processing through the fundus photos to identify the disc area. The input is the fundus photograph and the segmentation network would then use the CNN architecture to categorize the optic disc from the rest of the factors in the image. The function above called the Binary Cross Entropy Loss Function, then measures the differences between the anticipated and legitimate segmentation maps. This would then lead to penalization for incorrect predictions until the network is left with 100% accuracy in isolating the optic disc. Then finally the output of the segmentatio network would be a binary segmentation map that is only left with the optic disc therefore emphasizing its presence so that it is easier for further study, or analysis.

ADHD Severity Prediction Network

Figure 4 illustrates the architecture of the ADHD Severity Prediction Network. This is a visual representation of the process of the network using the imaging to determine the severity level of the patient's ADHD. For further explanation, The ADHD Severity Prediction Network is a deep learning model for classifying the severity of ADHD based on features extracted from optic disc images. It uses a ResNet-50 (He al al. 2016) model for feature extraction of the optic disc images and then a multi-layer perceptron hidden layers are set to process and analyze said features.

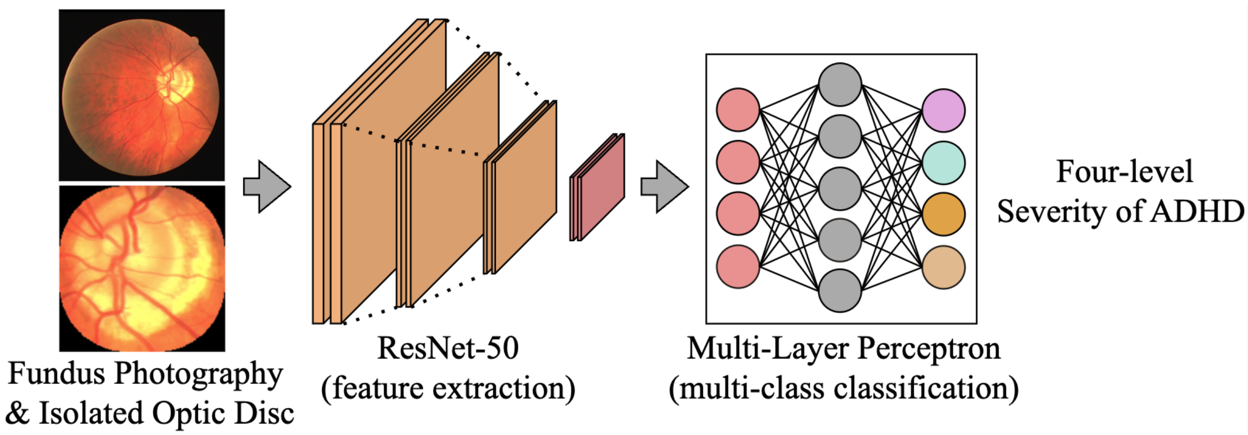


Figure 4. ADHD Severity Classification via Fundus Images and ResNet-50

The MLP includes layers with ReLU activations to put our results into one of four ADHD severity levels which are mild, moderate, severe, and very severe. The model is trained using a cross-entropy loss function, which minimizes the difference between predicted and calculated severity rates.

Equation 2: Cross-Entropy Loss Function

$$L_{ADHD} = -log_e(p)$$

Here, p denotes the predicted probability of the correct classification of the outcome. In this function, the probability and the classifications will be about the severity of ADHD. There are 4 levels: mild, moderate, severe, and very severe. Mild is when symptoms of ADHD are present but do not impact daily life or when people do not experience difficulties with their attention deficit or hyperactivities. Moderate is when symptoms start to slowly interfere with daily activities and become a struggle to manage.

When an individual is classified as Severe that's when ADHD symptoms become more pervasive and start to significantly impact life in multiple aspects, the level that has the most extreme parts of ADHD symptoms is Very severe, and the last and most intense level of ADHD.

Experimental Results

Fundus Dataset

The dataset used in this paper is the Fundus Image Data for Diagnosis of Psychiatric Disorders in Children and Adolescents. The samples used for training and evaluation comprise 37,145 samples from the control group and 63,250 samples from the ADHD group. The entire dataset is split into 80% for training and 20% for evaluation.

Evaluation Metric

To measure the performance of the proposed method, I utilized four evaluation metrics: accuracy, recall, precision, and F1 score. Accuracy provides a measure of correctness across all classifications. Recall indicates the model's ability to identify relevant cases, while precision focuses on the accuracy of positive predictions. The F1 score balances recall and precision which offers a comprehensive metric that reflects the model's overall performance.

Equation 3: Accuracy

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total}$$

Equation 4: Recall

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Equation 5: Precision

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Equation 6: F1-Score

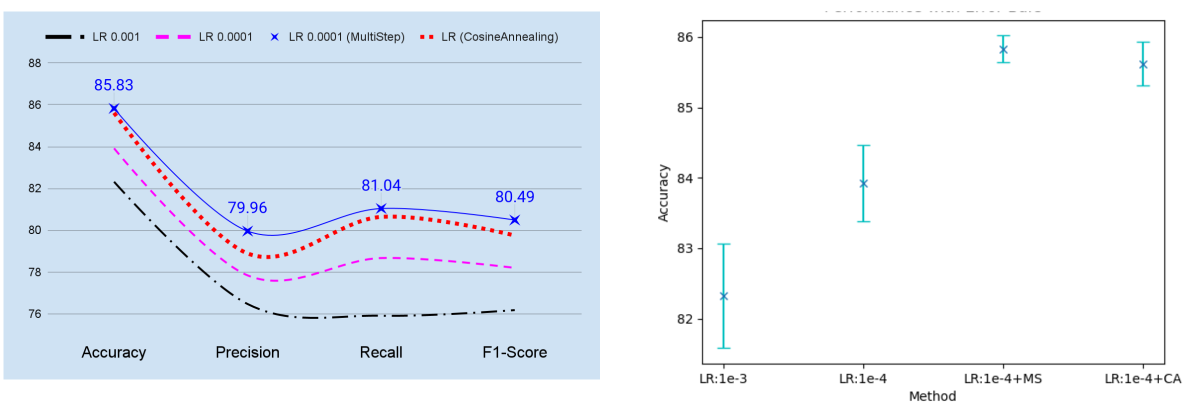
$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Evaluation Result

Table 1. Performance comparison with different training setups

Training Setup	Accuracy	Recall	Precision	F1-Score
Learning Rate: 0.001	82.32	76.47	75.91	**76.18**
Learning Rate 0.0001	83.92	77.84	78.67	78.2
Learning Rate 0.0001 (multistep schedule)	85.83	79.96	81.04	80.49
Learning Rate 0.0001 (cosine annealing)	85.62	78.89	80.64	79.75

The evaluation results show that the earring rate of 0.0001 with multistep scheduling performed best, achieving an accuracy of 85.835, with strong recall, precision, and an F1-score of 80.49. The cosine annealing also performed well but it didn't do as well as the multistep schedule. the baseline learning rate of 0.001 had the lowest performance, with an accuracy of 82.32% and an F1-score of 76.18. highlighting the advantage of a lower learning rate.



(a) (b)

Figure 5. (a): Performance comparison with different training setups and (b): K-fold cross-validation result

As expected, the trends in the metrics (Figure 5 a) support the notion that the multistep schedule is the most robust among the tested methods as it brings better results in all the metrics. Cosine annealing is also helpful but slightly lags behind the multistep schedule, while the lowest performance was observed with a baseline learning rate. This postulates that it is the higher learning rate that turns out to miss out on the crucial elements from the images of the fundus as compared to lower rates.

Again from the K-fold cross-validation (Figure 5 b), bordering on the conclusion from the discussion above, the multistep schedule not only achieves the maximum accuracy (~85.83%) but also displays lower error bars, so the performance is the most uniform and stable within various data folds. Cosine annealing is accurate but a little less forgiving on the boundaries of the error. The baseline learning rate (1e-3) shows both lower accuracy and larger error bars meaning that this approach is the least effective and consistent. Overall, by reducing the learning rate, adding a Little and large multiplying factors of the learning rate increases the fold, and partitioning the learning process also amputates performance drop and the most sustainable and efficient setup is attained through the use of the multistep schedule.

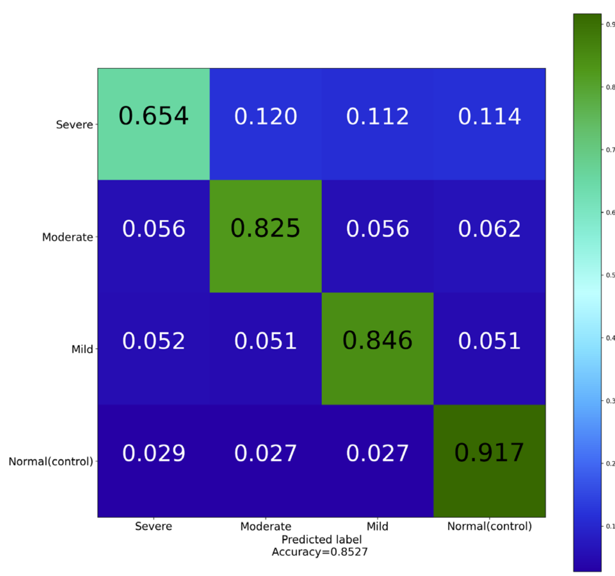


Figure 6. Confusion matrix evaluation

Lastly, I conducted a confusion matrix evaluation to assess the robustness of each prediction. Figure 6 illustrates the results of this evaluation. The true positive rates for normal, mild, and moderate severity were 91.7%, 84.6%, and 82.5%, respectively, which are high and comparable results. However, the severe category achieved a true positive rate of only 65.4%, indicating a need for further improvement in future studies. To enhance accuracy, I plan to collect more samples of severe cases in the future.

Conclusion

In this paper, I proposed a machine learning approach using fundus imaging to enhance the diagnostic accuracy for identifying and classifying ADHD. The system consists of two main things: an optic disc segmentation network and an ADHD severity classification network. These are designed to classify ADHD severity based on optic disc features extracted from fundus images. The proposed method effectively categorizes the severity of ADHD into four main levels: mild, moderate, severe, and very severe. The results show the model had achieved an accuracy of approximately 86% when using a learning rate of 1e-4 with a multistep schedule. In addition to these quantitative results, the proposed method has the potential for real-world application in ADHD diagnosis by providing a non-invasive and accessible screening tool. For future work, I plan to refine the system further for application in clinics and contribute to more efficient diagnosis and better treatment outcomes for ADHD patients.

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