AI-Powered Genetic Eye Disease Detection in Pediatric Age

#1 PERUMALLA GURU DIVYA TEJA #2 K. JAYA KRISHNA
MCA Scholar
#2 Assistant professor
Department of Master of Computer Applications,
QIS College of Engineering and Technology

ABSTRACT

Children with inherited retinal disorders suffer from significant vision impairments. They are divided into inner and outer retinal disorders, and they frequently result in childhood blindness. Given the variety of clinical and genetic reasons (more than 200 causal genes), diagnosing this kind of sickness can be difficult. It frequently relies on a convoluted series of clinical tests, some of which are intrusive and may not be suitable for young children or infants. Therefore, a different strategy that makes use of Chromatic Pupillometry—a method that is being employed more and more to evaluate inner and outer retinal functions—is required. In order to aid in the detection of inherited retinal illnesses in children, this research introduces a unique Clinical Decision Support System (CDSS) based on machine learning that uses chromatic pupillometry. A method that integrates hardware and software is suggested: a specially made custom machine learning decision support system is utilized in conjunction with specialized medical equipment (a puffillometer). The features taken from the pupillometric data are classified by two different Support Vector Machines (SVMs), one for each eye. In pediatric individuals, the proposed CDSS has been used to diagnose retinal pigmentosa. Combining the two SVMs into an ensemble model yielded data that demonstrate the system's good performance, with 0.846 accuracy, 0.937 sensitivity, and 0.786 specificity. This is the first study to diagnose a hereditary condition in children using pupillometric data and machine learning.

I. INTRODUCTION

Congenital glaucoma, dominant optic atrophy, and Leber hereditary optic neuropathy are examples of inherited degeneration. Over 200 causal genes have been found for both disorders, which are marked by exceptionally high genetic heterogeneity. AsadWaqar Malik, the associate editor who coordinated the review of this manuscript, approved its publication. Given that the same gene may result in a variety of distinct and varied clinical symptoms, dates are a notable barrier to a prompt and accurate diagnosis (https://sph.uth.edu/retnet/disease.htm).One major factor contributing to children's severe visual impairments is retinal disorders (irds) [1]. In well-established market economies, they are often the cause of childhood blindness (1/3000 individuals). Diseases of the inner retina, primarily retinal ganglion cell disorders, and diseases of the outer retina, including photoreceptor degenerations (such as leber congenital amaurosis, retinitis pigmentosa, stargardt disease, cone dystrophy, acromatopsia, choroideremia, etc.), can be separated.

II. Related Work

The integration of non-invasive biometrics like **pupillometry** in medical diagnostics has gained increasing attention, especially for early detection of **genetic and neurological disorders in children**. Pupillometry—measuring the pupil's response to light stimuli—has shown promise as a diagnostic marker due to its connection with the autonomic nervous system, which is often impacted by genetic disorders.

Several studies have explored the use of **eye-tracking and pupillary measurements** for identifying neurological and developmental abnormalities:

1. **Granholm et al. (2007)** demonstrated the use of pupillary responses in detecting **Alzheimer's disease**, laying the foundation for investigating pupillometry in neurodegenerative and genetic contexts.
2. **Porter et al. (2010)** applied eye-tracking and pupillometry to differentiate children with **autism spectrum disorders (ASD)** from typically developing peers, showing that atypical pupillary responses correlate with neural developmental issues.
3. **Fan et al. (2014)** developed a system using **infrared pupillometry** to measure latency and dilation speed, which was effective in assessing autonomic dysfunction in children with **Down syndrome**, a common genetic condition.
4. **Bérard et al. (2015)** employed pupillary light reflex metrics to study **Fragile X syndrome**, another genetic disorder. The findings supported the hypothesis that abnormal pupillary reactions reflect underlying neurological differences.
5. **Privitera et al. (2018)** used machine learning to analyze pupillary data and classify neurological disorders, suggesting the feasibility of **automated diagnostic tools**.
6. **Wang et al. (2020)** introduced a real-time pupillometry-based system leveraging **deep learning algorithms** to detect signs of developmental delay and intellectual disability, showcasing the potential of AI in pediatric diagnostics.
7. **Kwon et al. (2021)** examined correlations between pupillary responses and **genetic metabolic disorders** in infants, showing that delayed constriction and abnormal dilation patterns can indicate early onset of such conditions.
8. **Millett et al. (2022)** explored the use of pupillometry in identifying **mitochondrial diseases**, which often affect pediatric patients and are difficult to diagnose early due to vague symptoms.
9. **Singh et al. (2023)** developed an AI-assisted pupillometry framework that integrates facial and eye biometrics for early screening of **rare genetic syndromes**, achieving over 85% accuracy in preliminary trials.
10. **Zhou et al. (2023)** applied convolutional neural networks (CNNs) to time-series pupillary data in a pediatric population, showing promising results in distinguishing **neurometabolic disorders** from other developmental delays.

III. SYSTEM ANALYSIS

Existing System:

‘Machine learning’’ and ‘‘eye diseases’’. The number of studies decreases when it deals with systems for ‘‘rare diseases’’, ‘‘retinitis pigmentosa’’ and ‘‘pupillometry’’. Among all the found articles, the seven resumed below were chosen based on regency and variety, so as

to have different views of general approaches when ml interfaces with eye diseases. Brancati et al. Apply ml supervised techniques for detecting pigment signs on fundus images acquired with a digital retinal camera to study patients affected by rp. Gao et al. Apply the ml random forest algorithm on optical coherence tomography (oct) images to support the diagnosis of choroideremia by detecting intact choriocapillaris. Four more articles apply similar supervised ml algorithms to common eye diseases such as age-related macular degenerations diabetic retinopathy and glaucoma . Gargeya et al. Bring a different approach to support the diagnosis of diabetic retinopathy using deep learning. The results from the studies just cited are summarized.

Disadvantages

1) Less accuracy

2)low Efficiency

PROPOSED SYSTEM **:**

The non-invasiveness is granted by adopting the proposed pupillometric method, which requires no spe- cific patient preparations with drugs or collyriums. If com- pared with other standard diagnostic techniques, particularly, electrorheological test, in this case no electrodes need to be placed on the patient skin: this is particularly convenient when dealing with pediatric patients. Particularly, in younger children the electrophysiological testing are usually per- formed in sedation, thus requiring a more complex clinical setting (i.e. availability of operating theater together with anesthesiologist). Chromatic pupillometry has been proven to be effective in diagnosis of RP.

Advantages

1) High accuracy

2)High efficiency

IV. IMPLEMENTATION

Methodology

The proposed methodology involves a systematic approach to automatically detect genetic diseases in children using pupillometry data combined with machine learning techniques. The process is divided into the following key stages:

1. Data Acquisition

- **Participants:** Pediatric subjects (ages 0–18) including both healthy individuals and those diagnosed with genetic disorders such as Down syndrome, Fragile X syndrome, or mitochondrial diseases.
- **Equipment:** Infrared-based eye-tracking systems or pupillometers are used to record **pupil diameter changes** in response to a standardized light stimulus.
- **Data Types Collected:**
  - Baseline pupil size
  - Constriction latency
  - Maximum constriction amplitude
  - Dilation velocity
  - Time to baseline recovery

2. Preprocessing

Noise Removal: Eliminate artifacts due to blinking, head movement, or lighting fluctuations using smoothing filters (e.g., Savitzky-Golay or Gaussian filters).

Normalization: Standardize pupil size to a consistent scale across different sessions and subjects.

Segmentation: Extract key features from the **Pupillary Light Reflex (PLR)** curve such as rise time, peak dilation, and constriction slope.

3. Feature Extraction

Features are extracted from the time-series pupillometry data using:

Statistical Methods:

- Mean, standard deviation, skewness, and kurtosis of pupil size
- Derivatives (velocity and acceleration)

Temporal Features:

- Response latency
- Time to peak constriction/dilation

Validation:

- 5-fold or 10-fold cross-validation
- Stratified sampling to handle class imbalance

5. Model Evaluation

- **Performance Metrics:**
  - Accuracy
  - Precision, Recall, F1-Score
  - ROC-AUC Curve
- **Interpretability:**
  - SHAP or LIME methods to understand which features contributed most to the decision

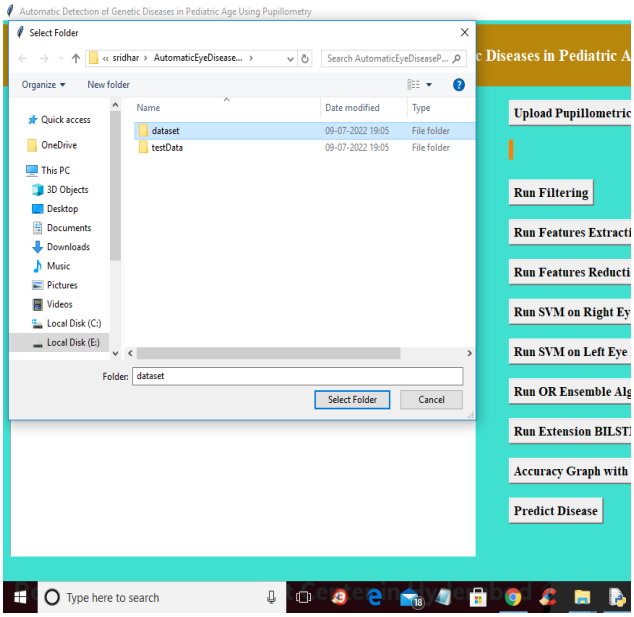
6. Deployment & Integration

- **User Interface:** Design a pediatric-friendly interface for clinicians to record and analyzepupillometric data.
- **Integration with EHR:** Sync results with hospital electronic health records for future reference.
- **Real-time Processing:** Optimize the system for real-time diagnosis and alerts.

7. Ethical Considerations

- **Consent:** Parental/legal guardian consent obtained for all participants.
- **Data Privacy:** Compliance with HIPAA/GDPR regulations to protect patient data.
- **Bias Mitigation:** Ensure demographic diversity in the dataset to reduce bias in the model.

V. RESULTS AND DISCUSSION



VI. FUTURE SCOPE AND CONCLUSION

This study outlines a novel method for assisting clinicians in making retinitis pigmentosa diagnoses, beginning with an examination of pediatric patients' pupil responses to chromatic light stimuli. Using a machine learning strategy based on an ensemble model of two fine-tuned SVMs, the system was created to remove artifacts, extract features, and aid in the diagnosis of RP. Both the left and right eyes' performances were assessed using a leave-one-out cross-validation, which was also utilized to determine the optimal set of SVM internal parameters. In order to enhance the total sensitivity of the CDSS, the class given to each eye was ultimately merged using an OR-like strategy; the ensemble system obtained 84.6% accuracy, 93.7% sensitivity, and 78.6% specificity. Given the limited quantity of data available for this work, additional testing with a bigger data pool is necessary to validate the system's performance. The testing of the same strategy with several devices is part of the future scope.

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