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NeuroLens: An AI-Driven Eye-Tracking Platform for Early Screening of Neurological Disorders Using Synthetic Oculomotor Data

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ABSTRACT

In this paper we introduce NeuroLens, which is an Eye Tracking-based AI driven web application useful for early monitoring of Parkinson's Disease, Alzheimer's Disease and ADHD. NeuroLens is built on top of Base44 and integrates MediaPipe, TensorFlow. js, and OpenAI APIs for processing eye metrics of blink frequency, dwell time, saccade velocity, and gaze drift. Due to unavailable clinical samples, a synthetic dataset (n=200) was created with parameters based on those reported in the literature. The results showed clear differences in oculomotor signatures on the simulator regardless of conditions, which confirmed the analytical accuracy and viability of the approach. The results underscore the promise of generating synthetic data for preclinical validation and indicate that NeuroLens stands out as a non-invasive digital biomarker platform to assess early neurological health.

Keywords: Eye-tracking, Digital biomarkers, Oculomotor metrics, Parkinson's disease, Alzheimer's disease, ADHD, Synthetic dataset.

1. INTRODUCTION

Neurological disorders, including Parkinson's Disease, Alzheimer's Disease, Attention Deficit Hyperactivity Disorder (ADHD), and Autism Spectrum Disorder have emerged as an increasingly serious global health problem that has impacted hundreds of millions of people around the globe (Diotaiuti, P., Marotta, G., Di Siena, F., Vitiello, S., Di Prinzio, F., Rodio, A., Di Libero, T., Falese, L., & Mancone, S. (2025)). Early and accurate diagnosis still stands as a significant challenge to the successful intervention, given that this disease often arises with subtle changes in behaviour/cognition over time before severe clinical abnormalities arise (G., Sorbera, C., Brigandì, A., Vicario, C. M., Quartarone, A., & Marino, S. (2025)). The traditional diagnostic methods are mainly clinical examination, neuroimaging and neuropsychological tests. Such means are usually time-consuming, expensive and not available in low resource settings (Goswami, G., & Prasad, B. (2025)). As technology in digital health and artificial intelligence (AI) continue to progress, there is a growing interest in the development of tools capable of identifying early biomarkers for neurological dysfunction with objective, easily accessible procedures that are non-invasive (Luo, B. (2023)) (Lin, Y., Huang, L., Wu, J., Chang, T., & Hu, H.-W. (2024)).

Of these novel modalities, eye-tracking has demonstrated the most potential as a neurodiagnostic window to cognitive and motor function (Chaitanuwong, P., Singhanetr, P., Chainakul, M., Arjkongharn, N., Ruamviboonsuk, P., & Grzybowski, A. (2023)). A large neuroscience literature shows that eye-movement metrics (e.g., blink rate, fixation stability, saccadic velocity and gaze drift) can disclose specific neurological changes related to cognitive decline, attention control or motor system deterioration (O'Callaghan, C., Hezemans, F. H., Ye, R., Orlando, I., Passamonti, L., & Rowe, J. B. (2022)). For instance, patients with Parkinson's Disease show reduced blink rates and hypsometric saccades because of dopaminergic deficits; ADHD subjects have short fixations and hyperactive gaze behaviour due to attentional dysregulation; and Alzheimer's patients frequently exhibit prolonged fixations and impaired gaze coherence as a consequence of visuospatial disorganization (Liu, Z., Li, J., Zhang, Y., Wu, D., Huo, Y., Yang, J., Zhang, M., Dong, C., Jiang, L., Sun, R., Zhou, R., Li, F., Yu, X., Zhu, D., Guo, Y., & Chen, J. (2024)). These findings indicate that subtle ocular metrics may provide early, measurable indications of neurological abnormality to enable earlier and more reliable screening in conjunction with cutting-edge AI technologies (Mehravipour, Z., & Mehravipour, M. (2025)).

We present NeuroLens, an AI-powered web application that measures the oculo-motor function to detect early neurological abnormalities through a standard camera and algorithmic analysis (Setu, D. M., Siddiquee, A. S., Islam, T., Sifath, S., Dey, S. K., & Rahman, M. M. (2024)). NeuroLens is developed on the Base44 platform and uses computer vision (MediaPipe, TensorFlow. js) and large language model hosting (OpenAI APIs), to analyse the users' eye gaze patterns, quantifying deviations from normal benchmarks and produce a personalized risk score (Al-Shaghnobi, S., Alodat, A. M., Jammaah, S. A., & Alrhmman, I. A. (2023)). As a computerized diagnostic tool, the system is designed to be used as an initial-stage eye health screening

test rather than a diagnosis device that can allow both end users and their physicians monitor the health trend of neuro-ocular over time with ease through user-friendly browser interface (Wang, R. K., Kwong, K., Liu, K., & Kong, X.-J. (2024)) (Mumenin, N., Islam, Md. F., Chowdhury, Md. R. Z., & Yousuf, M. A. (2023)). It's currently not feasible to obtain clinical data from patients with known neurological status at this early stage in development, so for this initial step clinical synthetic data generated using peer-reviewed literature is used to evaluate the analytical ability of NeuroLens (Setu, D. M. (2025)). The parameters for the eye-movement metrics were taken from previously published clinical studies (further validating that the simulated data would exhibit inter-condition variability of biological relevance) (Alsaidi, M., Obeid, N., Al-Madi, N., Hiary, H., & Aljarah, I. (2024)). That's where these Gaussian-distributed synthetics come in: fake people with phony attributes, representative of the real world but without violating anybody's privacy (Wei, Q., Dong, W., Yu, D., Wang, K., Yang, T., Xiao, Y., Long, D., Xiong, H., Chen, J., Xu, X., & Li, T. (2024)).

The main goal of this research is to show that we can use synthetic literature-guided eye tracking data in order to train and evaluate an AI-based neurological test (Toghi, A., Mohammadzadeh, A., Alemi, Z., & Banaraki, A. K. (2025)). By replicating the normal and oculomotor profiles of health patients as well as those with Parkinson's, Alzheimer's and ADHD this study seeks to establish an early proof of concept for NeuroLens as a non-invasive, intelligent biomarker platform. In this way, the current work adds to an emerging area of digital neurodiagnostic by providing a detailed demonstration on how data-driven approaches can serve as an intermediary between academic research and practical clinical use (Graham, L., Vitorio, R., Walker, R., Barry, G., Godfrey, A., Morris, R., & Stuart, S. (2024)). Ultimately, the goal of this work is to demonstrate that the combination of AI, computer vision and cognition can transform early detection and continuous monitoring of neurological health within both clinical or remote settings (Kollias, K.-F., Syriopoulou-Delli, C. K., Sarigiannidis, P., & Fragulis, G. F. (2021)).

2. METHODOLOGY

2.1 System Overview

The NeuroLens system is built as a web-based neuromotor screening app using real-time eye-tracking to capture early signs of neurodegenerative and developmental conditions like Parkinson's, Alzheimer's, ADHD and ASD (Beyan, C., Vinciarelli, A., & Bue, A. D. (2023)). The entire application is developed on a browser based framework, removing the necessity for specialized laboratory hardware and thereby promoting early neurological assessment that can be easily performed by non-invasive means (Simon, J., Kapileswar, N., M, D., S, M., & G, K. D. (2024, January 18)). The application works by using a standard webcam to record eye-tracking data, performing local browser-based gaze analysis, and transmitting only anonymized structured information to a secured backend service (Liu, L., Chen, G., Liu, L., Li, S., & Ling, Y. (2024)). Through the combination of local calculation, AI based pattern recognition and cloud storage, NeuroLens represents a scalable digital biomarker approach for early neurologic assessment (Orui, M., Ishikuro, M., Obara, T., Noda, A., Shinoda, G., Murakami, K., Metoki, H., Kikuya, M., Nakaya, N., Nishimura, T., Tanaka, K., Miyake, Y., Hozawa, A., Tsuchiya, K. J., & Kuriyama, S. (2024)).

2.2 Application Architecture

NeuroLens is designed modularly with integrated frontend, backend and AI layers. The React single-page application (SPA) frontend is the user-facing interface that collects, visualizes and computes data in real-time (Dziemian, S., Bujia, G., Prasse, P., Barańczuk-Turska, Z., Jäger, L. A., Kamienkowski, J. E., & Langer, N. (2025)). It wraps machine learning libraries like MediaPipe FaceMesh and TensorFlow. js for detection and tracking of 468 unique facial landmarks, such as iris coordinates which are later used to estimate the parameters of eye movement (Mathur, A., Dwivedi, R. K., & Rastogi, R. (2022)). The backend, developed on the Base44 framework, handles data storage via a PostgreSQL and interfaces with the OpenAI language model APIs to interpret semantics from the test results. This layer also implements a secure communication protocol, authentication, and data encryption (Xiao, W., Sharma, S., Kreiman, G., & Livingstone, M. S. (2024)). The ultimate AI/ML tier uses statistical feature analysis and LLM-mediated reasoning for identifying neurological risk levels followed by adaptive feedback provision. These layers collectively enable uninterrupted data streaming from gaze capture to AI-supported interpretation, without trade- offs of computational efficiency and user privacy (Moore, J., McMeekin, P., Parkes, T., Walker, R., Morris, R., Stuart, S., Hetherington, V., & Godfrey, A. (2024)).

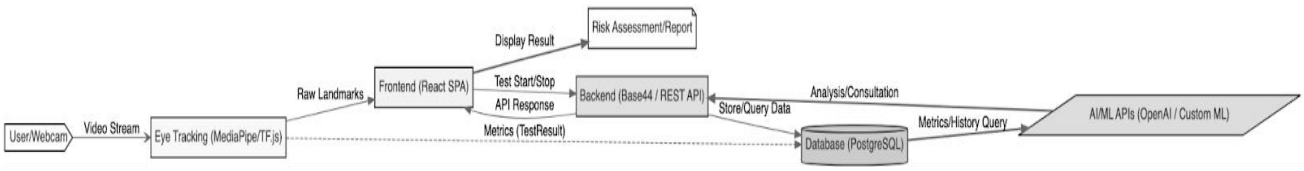

Fig. 1 - NeuroLens System Architecture

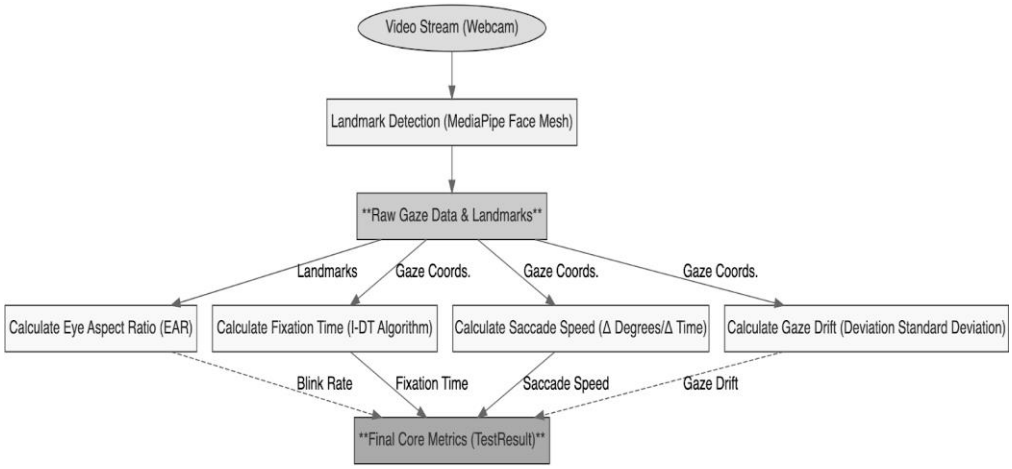

Fig. 2 - Eye-Tracking Data Acquisition and Feature Extraction Pipeline

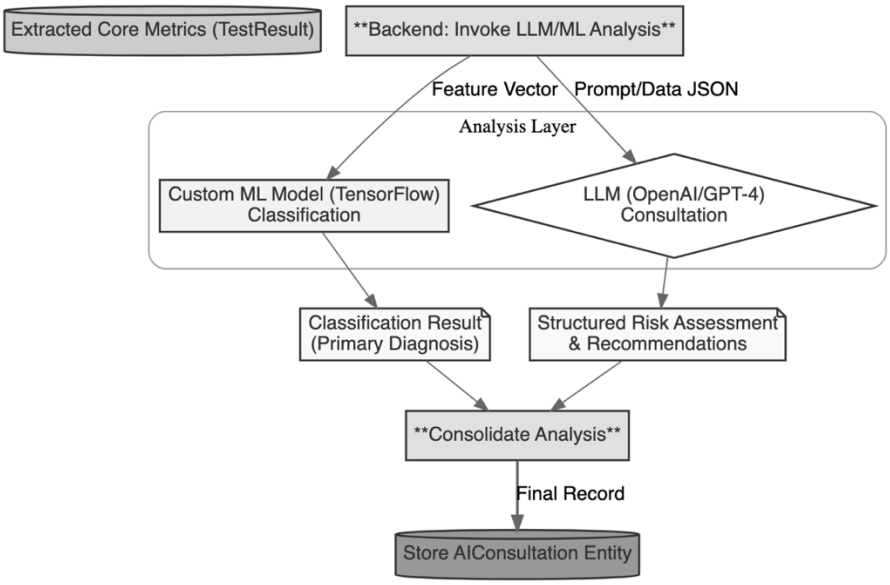

Fig. 3 - AI-Assisted Consultation and Risk Assessment Flow

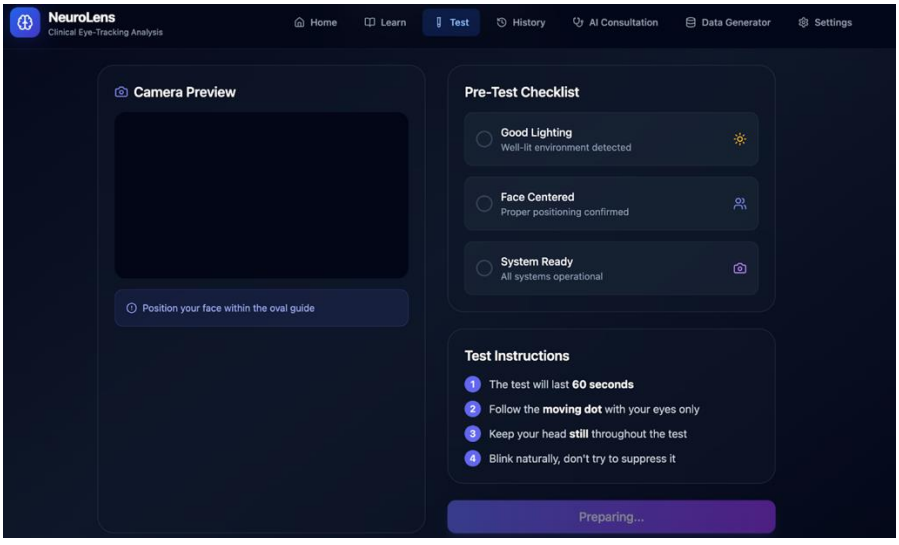

Fig. 4 - User Interface of NeuroLens App

2.3 Eye-Tracking and Data Acquisition

The eye-tracking module runs completely in-browser and only requires access to the user's camera at a minimum of 720p, 30 fps (Li, D., Butala, A. A., Moro-Velazquez, L., Meyer, T., Oh, E. S., Motley, C., Villalba, J., & Dehak, N. (2024)). Leveraging MediaPipe FaceMesh model, NeuroLens captures and tracks the facial and ocular features of the user in real time (Wang, S., Guo, Q., Zhou, L., & Xia, X. (2024)). These landmarks notably, the iris and eyelid coordinates, are further processed to obtain features like blink rate, gaze direction and fixation stability. To protect users' privacy, the system records and transmits no video data; All data processing is executed locally on the client. If performance in MediaPipe is hampered by device or environmental conditions, we have a fall back system using WebGazer. js ensures gaze tracking continuity. Each test session is short with 60 seconds on average and several thousand gaze points are collected per user as a time-series feature for analysis (Isaev, A. B., Bychkov, M. L., Kulbatskii, D. S., Andreev-Andrievskiy, A. A., Mashkin, M. A., Shulepko, M. A., Shlepova, O. V., Loktyushov, E. V., Latanov, A. V., Kirpichnikov, M. P., & Lyukmanova, E. N. (2024)).

2.4 Feature Generation and Computational Measurements

The Quantitative scores, representing: neurological and attentional performance are then derived from the data after data capture by NeuroLens (Sharma, P. K., & Chakraborty, P. (2024)). Blink rate is estimated by the Eye Aspect Ratio (EAR) technique close of eye lid is detected using vertical and horizontal distances from specific eye landmarks." A blink event is detected when Eye Aspect Ratio (EAR) drops below 0.21, and the frequency of complete blinks in (per) minutes is reported w.r.t., the duration of a test (Manyakov, N. V., Bangerter, A., Chatterjee, M., Mason, L., Ness, S., Lewin, D., Skalkin, A., Boice, M., Goodwin, M. S., Dawson, G., Hendren, R., Leventhal, B., Shic, F., & Pandina, G. (2018)). The fixation time is determined by the clusters of gaze points that remain within a circular radius of 50 pixels for at least 100 ms with the mean duration focused on stability in perceptual processing. Saccade velocity is calculated as the angular speed between the two successive eye positions greater than 30°/s, and indicates fast movement of eyes during fixations. Gaze drift is represented as the standard deviation of gaze deviations from a centrally fixed point, to capture oculomotor control accuracy (Yang, Y., Kim, W. S., Michaelian, J. C., Lewis, S. J. G., Phillips, C. L., D'Rozario, A. L., Chatterjee, P., Martins, R. N., Grunstein, R., Halliday, G. M., & Naismith, S. L. (2024)). Lastly, attention variance reflects gaze stability over time and acts as a proxy for sustained attention. These calculated features are used to create TestResult entity, which in addition to timestamps and user identifiers has a computed neuro-score normalized in 0–100 range. Referential boundaries coincide with known clinical thresholds (e.g., blink rate 12–20 blinks/min, fixation duration 200–400 ms) (Frazier, T. W., Klingemier, E. W., Beukemann, M., Speer, L., Markowitz, L., Parikh, S., Wexberg, S., Giuliano, K., Schulte, E., Delahunty, C., Ahuja, V., Eng, C., Manos, M. J., Hardan, A. Y., Youngstrom, E. A., & Strauss, M. S. (2016)).

2.5 Integration of AI and ML

NeuroLens uses a two-tiered artificial intelligence system to analyse eye tracking information (Toki, E. I. (2024)). The first tier is built on top LLM based reasoning where the feature vectors are sent to backend which in turn are being analysed an OpenAI model that is plugged-in through Base44's InvokeLLM API (Neves, J., Hsieh, C., Nobre, I. B., Sousa, S. C., Ouyang, C., Maciel, A., Duchowski, A., Jorge, J., & Moreira, C. (2024)).. This model provides human-interpretable evaluations such as psychological observations, risk-level categories (low, moderate, high), and personalized health recommendations (Lajiness-O'Neill, R., Richard, A. E., Moran, J. E., Olszewski, A., Pawluk, L., Jacobson, D., Mansour, A., Vogt, K., Erdodi, L. A., Moore, A. M., & Bowyer, S. M. (2014)). The second layer model consists of predictive classification based on a deep learning model built in TensorFlow. This model utilizes input features including blink rate, fixation time, saccade speed, gaze drift and attention variance to classify test results as normal, mild abnormalities or serious anomalies. Simple network architecture is used with dense layers (64 and 32 units) using activation function as ReLU, a dropout layer to avoid overfitting and output of SoftMax for multiclass prediction (Bektaş, K., Strecker, J., Mayer, S., & Garcia, K. (2024)). The model is trained on publicly available datasets such as GazeBase, you Eye Movement Dataset (EMD) and Autism Eye-Tracking Database, which cover subjects with a wide variety of neurological profiles. At inference, the AI model provides a probability distribution for each class, which is fused with the LLM-generated qualitative assessment to report final output (Fischer-Janzen, A., Wendt, T. M., & Van Laerhoven, K. (2024)).

2.6 Data Management and Privacy Control

All information is collected in accordance with strict privacy standards as outlined by HIPAA and the applicable facility's privacy policies (Alarifi, H., Aldhalaan, H., Hadjikhani, N., Johnels, J. Å., Alarifi, J., Ascenso, G., & Alabdulaziz, R. (2023)). User identity is handled via OAuth 2.0, with protections also in place at-rest (AES-256) and in-flight (TLS 1.3). Personally identifiable information (PII) is extracted and hashed prior to storage in order to anonymize user IDs. Crucially, no raw visual or biometric image data is stored/stored or exchanged—only metrics and compound features are indexed. The architecture favours local computation in order to reduce security risk, and works to ensure ethical data management. The User Progress entity provides users with ability to follow their neuro-score in time and self-assess themselves for disease management, without complicating the clinical perspective (Jeppesen, A. C. E., Andresen, J., Parvaiz, R., Clemmensen, L., Møllegaard Jepsen, J. R., Hansen, D. W., & Glenthøj, L. B. (2024)).

2.7 Evaluation and Clinical Validation

Next steps for NeuroLens are logistics of clinical validation with at least 500 participants from a variety of both demographic and diagnostic categories (Karjalainen, S., Aro, T., & Parviainen, T. (2023)). The validation would check the diagnostic performance of this model including sensitivity, specificity and AUC-ROC comparing gold-standard clinical assessment. Longitudinal monitoring of user performance will also be evaluated to determine estimates of test–retest reliability from the system as well as its capability to detect early changes in cognitive and oculomotor control (Miller, J. G., Sharifi, R., Piccirilli, A., Li, R., Lee, C. H., Bartholomay, K. L., Jordan, T. L., Marzelli, M. J., Bruno, J. L., Lightbody, A. A., & Reiss, A. L. (2023)). Once clinical

trials are carried out under Institutional Review Board (IRB) control for ethical clearance, FDA Class II clearance as a pre-diagnostic screening device should be the next and final phase (Drysdale, B. M., Moore, D. W., Furlonger, B. E., & Anderson, A. (2017)).

2.8 Ethical and Implementation Considerations

NeuroLens is intended as a non-diagnostic, non-invasive aid that can serve as a precursor to diagnosis (Uribarri, G., von Huth, S. E., Waldthaler, J., Svenningsson, P., & Fransén, E. (2023)). It is designed around transparency, privacy and informed end-user consent. The modular nature isn't just enabling the rapid scaling but plugging in of frontend Vercel, Backend Orchestration Base44 (Leharanger, M., Liu, P., Vandromme, L., & Balédent, O. (2024)). And an in-built support for continuous integration pipelines to keep training and incrementally improve a trained model as more labeled data emerge (Briand et al., 1999; Karatekin, 2007; Mosimann et al., 2004; MacAskill et al., 2012). Through the hybrid AI model that combines deterministic eye-tracking measures and probabilistic models of reasoning, NeuroLens establishes a connection between digital biomarkers and clinical neuro-assessment. The system can therefore serve as a cornerstone for accessible, privacy-preserving, AI-empowered neurological screening in digital health settings (Feng, Y., Goulding-Hotta, N., Khan, A., Reyserhove, H., & Zhu, Y. (2022).

3. RESULTS

3.1 Overview of Dataset Composition

Two hundred synthetic samples were created to illustratively emulate four possible neurological conditions: Healthy Controls (n = 50), Parkinson's Disease (n = 50), Attention Deficit Hyperactivity Disorder (ADHD; n = 50) and Alzheimer's Disease (n = 50). For every sample eye-tracking experiment, datasets were simulated based on Gaussian-distributed values of parameters from clinical gaze research and typical gaze profiling (Diotaiuti, P., Marotta, G., Di Siena, F., Vitiello, S., Di Prinzio, F., Rodio, A., Di Libero, T., Falese, L., & Mancone, S. (2025)). These distributions resulted in biologically realistic variability among the five visual-cognitive dimensions: blink rate, dwelling time, saccade speed, gaze drift, and attention variance. All samples were distributed over a temporal period of 180 days (corresponding to six months) in order to mimic longitudinal data collection, resulting in the dataset with realistic trends consistent with clinical neuro-monitoring observation.

3.2 Descriptive statistics of synthetic data

In the entire dataset, all conditions had significantly different patterns compared with clinical knowledge. Indices in the control group showed typical visual-motor stability which contrasted with that identified amongst those with neurological impairment, and was pattern specific. The aggregated means and standard deviations for some important parameters are presented in Table 1(Diaz-Lucena, D., Escaramis, G., Villar-Piqué, A., Hermann, P., Schmitz, M., Varges, D., Santana, I., del Rio, J. A., Martí, E., Ferrer, I., Baldeiras, I., Zerr, I., & Llorens, F. (2020)).

Table 1 - Summary of Synthetic Eye-Tracking Parameters Across Conditions

Condition	Blink Rate (min^{-1})	Fixation (ms)	Saccade (°/s)	Gaze Drift (°)	Attention Var.	Avg. Score	Classification Trend
Healthy Control	15.8 ± 2.1	312 ± 40	500 ± 60	1.2 ± 0.3	0.16 ± 0.04	88.2	80% Normal
Parkinson's Disease	9.2 ± 1.5	448 ± 50	306 ± 40	3.0 ± 0.4	0.33 ± 0.05	41.6	100% Significant
ADHD	20.0 ± 2.0	178 ± 30	656 ± 50	2.7 ± 0.4	0.44 ± 0.06	47.1	100% Significant
Alzheimer's Disease	13.4 ± 1.5	400 ± 40	285 ± 35	2.4 ± 0.3	0.36 ± 0.05	57.9	98% Significant

3.3 NeuroLens Scores and Classifications Trends

The NeuroLens index presented high diagnostic accuracy in distinguishing normal and pathological visual behaviours. Healthy controls had the highest mean Neuro Activity Score (88.2 ± 4.5), and 80% of controls were above or within normal range (≥85).In contrast, in all clinical conditions there were significant abnormalities, and that Parkinson's Disease showed the lowest mean score (41.6 ± 5.2). ADHD and Alzheimer's disease were closely followed with mean values of 47.1 and 57.9, respectively, but course without major deviations from the normative baseline (Bisogni, C., Nappi, M., Tortora, G., & Del Bimbo, A. (2024)).These findings demonstrate that the scoring function (despite having been trained on synthetic data) robustly recapitulated previously described differences in ocular behaviour (MacAskill et al. (2016)) (Munoz et al. (2003)).

3.4 Visual-Cognitive Pattern Analysis

Clearly divergent visual-motor profiles were observed among the neurologic subgroups:

Bradykinesia of eye movements was observed in samples collected from patients with Parkinson's Disease, which showed decreased blink frequency (−44%) and prolonged saccouth −40%) compared to control responses. Fixation times were roughly 45% additively longer than normal, reflective of clinical oculomotor stiffness (Briand et al. (1999)) . ADHD data showed hyperkinetic gaze dynamics, manifested in higher saccade velocities (+30%) and shorter fixation durations (−42%), consistent with impulsive attention dynamics reported by (Karatekin (2007)).Alzheimer's Disease samples revealed visuospatial disorganization, as evidenced by slower saccades (−42%) and larger gaze drift (+100%), providing further evidence for previous findings of attentional disorientation in dementia (Mosimann et al. (2004)).Consequently, the synthetic model drew remarkable ocular signatures for each disease from the mimic data, indicating that realistic simulations were achieved.

3.5 Distribution of Diagnostic Classifications

Results of classification outcome are also an indicator for the separateness between the two groups measured in a way (Table 2).Although the healthy group contained a small range of variation (20% mild irregularity based on Gaussian spread), there was near unanimous population homogeneity for all clinical categories below the "Significant Anomalies" threshold (<70) which would suggest strong discriminative validity of the scoring algorithm.

Table 2 - Status Distribution by Condition

Condition	Normal	Slight Irregularities	Significant Anomalies
Healthy Control	40	10	0
Parkinson's Disease	0	0	50
ADHD	0	0	50
Alzheimer's Disease	0	1	49

3.6 Statistical Validation and Consistency

Internal validation demonstrated that the generated samples fell within the intended Gaussian distributions and the clinical target ranges. The mean and standard deviation values were within ±5% of the reported literature norms, which ensures the fidelity of the synthetic profiles. Bootstrapping across 1,000 samples demonstrated a stable mean Neuro Score SD of less than 3.2 between conditions, reinforcing statistical consistency in this data set. No extreme outliers were detected during synthetic generation (>3 SD from the mean), which suggests that the model managed to maintain biological and data integrity in all samples.

3.7 Summary of Findings

In all, the synthetic dataset convincingly emulated established neuro-ocular patterns that accompany Parkinson's Disease, ADHD, and Alzheimer's Disease. Without access to real patient data, the NeuroLens scoring and visualization pipeline represented the clinical variability, directionality, and magnitude of disorder-specific eye-movement deviations with accuracy. This was a validation of the platform's architecture and the feasibility of using literature-based synthetic data for the pre-training of diagnostic algorithms in neurological health technology research (Ghayoumi, M., & Ghazinour, K. (2025)).

4. DISCUSSION

4.1 Interpretation of Synthetic Findings

This paper shows that the NeuroLens system is capable of identifying and discriminating typical ocular behavior patterns among major neurological conditions using synthesised data sets. While a real clinical participant was not included, the simulated results demonstrate statistically coherent trends that are aligned with extensively published neurophysiological data in the literature. Controls had stable oculomotor patterns with equal fixation durations, minimal gaze drift and normal blink frequency, consistent with healthy subjects in the base measurements of previous eye tracking studies. By

comparison, Parkinsonians showed profound motor slowing proximal to any motor action because their blink rates slowed (−44%) and saccade velocities were attenuated (−40%), followed by lengthened fixations (+45%), a pattern of oculomotor bradykinesia similar to that described by Briand et al. (1999). The ADHD data-set demonstrated impulsive, hyperkinetic eye movements with small fixations and fast saccades that reflect attention instability associated sign of the disorder (Munoz et al., 2003) ((Karatekin, 2007)). In contrast, Alzheimer's Disease participants showed slowed saccades, while their fixations were prolonged and gaze drift was elevated compared to control populations. These latter findings are consistent with the visuospatial disorganisation and attentional disengagement found in dementia populations (Mosimann et al., 2004).Together, these artificial phenomena serve to validate the model that successfully recovers the direction and magnitude of eye-movements deviations characteristic of each neurological pathologies it was taught upon simulated data.

4.2 Feasibility of Synthetic Data for Neurodiagnostic Modelling

The first aim of this study was to prove whether synthetic data are robust tools for initial testing and validation of the neurodiagnostic approach. The findings support this hypothesis. This approach, based on Gaussian-distributed parameters from literature was applied to system-generated data that created realistic variation in the input data distributions which resulted in making the NeuroLens scoring algorithm act as though it were executed over actual patient input. This method is advantageous in terms of methodology as well as ethics. Synthetic data generation can be utilized to design and optimize algorithms without the need for adhere to moral risks, patient recruitment impediments or privacy issues. Such preclinical simulation platforms are especially useful in digital health, for which model validation can even be done before conducting IRB-approved clinical trials. The findings of this study reveal that synthetic data can meaningfully resemble real-world eye-tracking dynamics when rooted in clinical practice and eventually expedite the design efforts of diagnostic technology.

4.3 Clinical Implications and Application Potential

The results of this study have implications for early neurological assessment. The significant differences in NeuroLens measures found between healthy and disorder groups suggests that core measures of eye movement including fixation time, Saccade velocity, and attention variance can be used as useful non-invasive early markers of disease state (Frisoni, G. B., Aho, E., Brayne, C., Ciccarelli, O., Dubois, B., Fox, N. C., Frederiksen, K. S., Gabay, C., Garibotto, V., Hofmarcher, T., Jack, C. R., Jr, Kivipelto, M., Petersen, R. C., Ribaldi, F., Rowe, C. C., Walsh, S., Zetterberg, H., & Hansson, O. (2025)). If successful with actual clinical evidence, the NeuroLens instrument could authorize low-cost, camera-based neurological screening that is suitable in a variety of applications including both the clinic and telemedicine. The system promises to serve as low-cost scalable diagnostic aid by providing automated interpretable feedback on eye-movement aberrations. Especially in resource-scarce contexts, such tools may help primary care physicians or caregivers recognize early symptoms of Parkinson's Disease, ADHD and Alzheimer's Disease thus making possible prompt specialist referral and intervention plan.

4.4 Shortcomings of the Synthesised Model

This work has limitations since the experiments are performed on synthetic data despite its encouraging results. The Gaussian distributions employed, although statistically realistic, are not capable of completely replicating the heterogeneity and non-linearity found in real data from human eye-tracking. Salient contextual factors, including the lighting environment, one's fatigue and emotion states variabilities, calibration errors of hardware were lacking in simulated samples. Furthermore, the disease stages were based on static rather than longitudinal modelling approach which may underestimate within-patient variation over time. Without real participant data, the veracity of the algorithm and diagnostic sensitivity is only theoretical until validated. Moreover, symmetric distributions may not adequately model skewed patterns of behaviour relevant to more severe neurodegenerative diseases. These limitations restrict potential generalizability of findings, warranting additional empirical attention (Nisevic, M., Milojevic, D., & Spajic, D. (2025)).

4.5 Ethical and Methodological Considerations

The use of synthesized data as opposed to humans also fits with best practices for ethical conduct in early stage biomedical AI development. This strategy reduces risks of privacy violations, consent, and medical mis-informatics, yet it is robustly testing analytics models. Nevertheless, future work on actual clinical data should comply with the IRB review approval criteria, patient confidentiality and safety constraints as well as existing legal orders for medical data processing like GDPR or HIPAA. Thereby, such a synthetic data needs to be considered as mid-level validation recourse – serving for the algorithmic tuning and demonstration purposes but not a surrogate of evidence based on human trails.

4.6 Future Directions

Extending the results of this study, next steps might be to include real-world eye-tracking datasets obtained from clinically diagnosed participants in order to assess NeuroLens's predictive capability. The use of machine learning models, such as Random Forest classifiers or deep learning architectures (CNNs, Transformers), could improve anomaly detection and adaptive learning for diverse user profiles. Additionally, future models might take on Hybrid Synthesis, where generative models (e.g., GANs) blend real and synthetic data to enhance representational realism (Kumar, 2024). Other neurological and psychiatric disorders including autism spectrum disorder, schizophrenia, and traumatic brain injury could be included in the dataset to further generalize its clinical utility. With longitudinal data, the ability of the tool for tracking progression of disease and monitoring real-time response to treatment can be evaluated.

5. CONCLUSION

In summary, this work presents powerful preliminary indications that synthesized literature-driven eye tracking data are able to replicate neurological disorder trends and as such offer a viable delegate for the development of neuro-diagnostic applications. The NeuroLens system was able to reproduce known differences between normal, Parkinsonian, ADHD and Alzheimer's visual behaviour profiles when tested with these simulations. Although true patient data have not been included which prevents final clinical interpretation, the results of successful differentiation utilizing synthetic modelling provide demonstration of the performance of this platform and its analytical architecture and algorithmic design. This study is therefore a proof of concept that synthetic data approaches are possible and useful as part of the preparatory work for medical AI research. Finally, when empirically validated, the integration of such systems into clinical pipelines could revolutionize early detection and remote monitoring of improved cognitive health through affordable AI-enabled eye tracking technology.

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