

## Digitizing Binocular Vision Diagnostics via EyeQ Platform: A Study on Algorithmic System Architecture for Convergence Insufficiency (CI) Detection

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### Abstract:

**Background:** Convergence Insufficiency (CI) is a complex neuromuscular visual disorder traditionally diagnosed using manual, subjective instruments like the RAF Rule, which heavily rely on examiner estimation and patient response times. **Methods:** To address these clinical limitations, this study introduces the EyeQ platform, an innovative diagnostic framework that integrates eye-tracking technology with deep learning architectures powered by the TensorFlow framework. A single-blind comparative study was conducted involving 50 participants. A broad, heterogenous age spectrum (ranging from 6 to 82 years) was intentionally selected to rigorously validate the system's algorithmic adaptability and robustness across diverse demographic profiles and age-related physiological ocular variations. The platform utilizes a dynamic "Approach-Recede" mechanism to monitor ocular neuromuscular responses and isolate precise Break and Recovery Points. Automated diagnostic outcomes were benchmarked directly against independent clinical evaluations performed by a certified optometrist. **Results:** The EyeQ platform demonstrated high diagnostic efficacy, achieving an overall accuracy of 94% by matching the specialist's clinical findings in 47 out of the 50 cases. Crucially, detailed clinical analysis revealed that the 6% statistical variance (3 cases) was entirely attributed to physical anatomical obstructions—specifically, two cases of ptosis and one case of severe eyelid edema—which occluded the digital region of interest (ROI) and hindered feature extraction,

rather than systemic or algorithmic failure. **Conclusion:** The EyeQ system provides exceptional digital objectivity and reliability, eliminating subjective examiner bias and establishing a standardized digital database for longitudinal vision tracking. Given its high diagnostic precision and architectural consistency, the platform is highly qualified to It shows potential for use in large-scale screening applications in the future, subject to its validation in multiple centers.

**Keywords:** Convergence Insufficiency, Artificial Intelligence, Eye Tracking, Digital Diagnostics, Optometry.

### Introduction:

Convergence Insufficiency (CI) is a complex sensory-motor disorder of the visual system characterized by the inability to maintain proper ocular alignment during near-vision tasks [1,6,8]. Traditionally, clinical diagnosis relies on manual tools such as the RAF Rule, which are highly dependent on the examiner's subjective estimation and the patient's reaction time [2,3]. The research problem lies in the technological gap between traditional clinical examination and modern digital needs [4].

To address this limitation, the EyeQ platform was developed to bridge this gap by providing Objective Measurements based on real physical data, thereby reducing human error and providing a precise digital database for diagnosis. This paper presents the scientific and engineering foundations of the EyeQ platform, an advanced diagnostic system that integrates Eye Tracking technology with Artificial Intelligence-based image processing. The platform aims to automate Convergence Insufficiency (CI) testing by analyzing the ocular neuromuscular response during the physical movement of the device. Ultimately, this paper discusses the system's infrastructure, the innovative examination methodology, and the criteria used to validate performance efficiency.

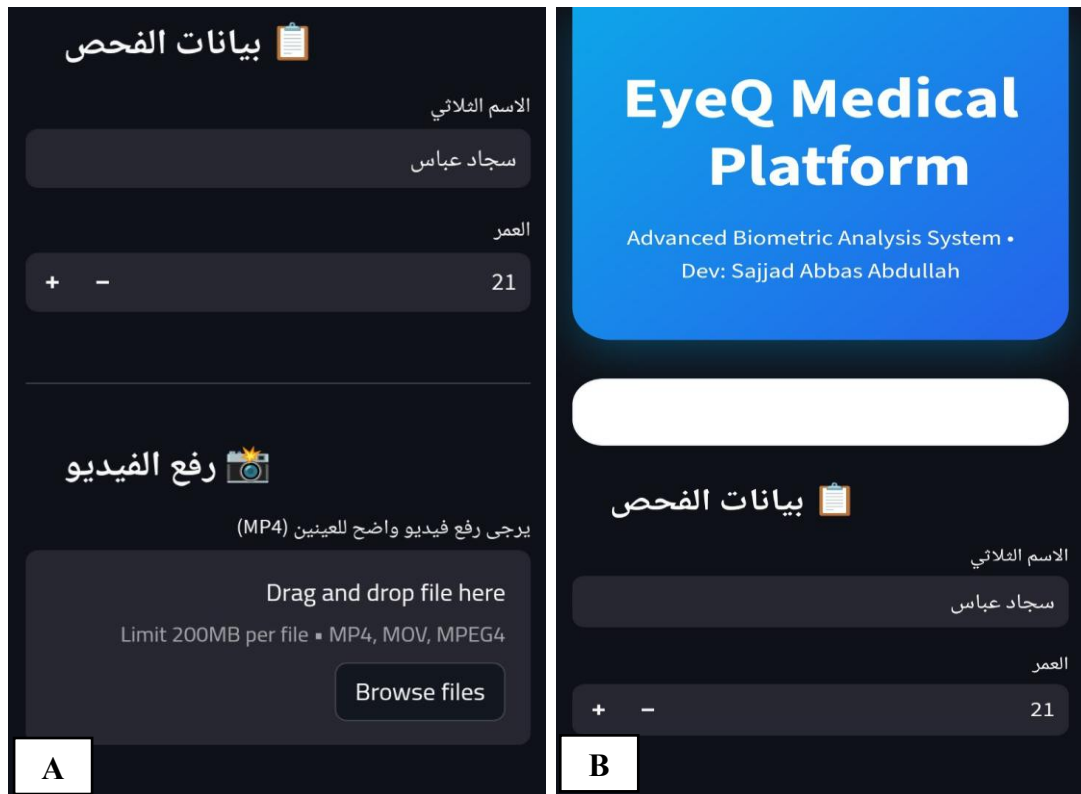


Image 1. EyeQ Medical Platform Interface. (A) User interface for entering patient demographic data and uploading an eye examination video. (B) Main application screen showing the platform dashboard and patient information panel.

## Materials

### Study Design and Sampling

To ensure scientific reliability, a single-blind comparative pilot study was designed. The research sample included 50 carefully selected participants who underwent comprehensive visual examinations to rule out any other organic diseases. This single-Prospective single-blind comparative pilot study was conducted between August 2025 and March 2026. During this period, 50 individuals underwent a traditional clinical assessment by a licensed optometrist, as well as an automated assessment using the EyeQ device. The examining optometrist was blinded to the EyeQ results until completion of all clinical assessments. Data were collected, processed, and statistically analyzed during the same study period. Sample size calculation was performed using G\*Power 3.1 software assuming an effect size of 0.5,  $\alpha=0.05$  and power=80%.

### Inclusion Criteria

- Age >6 years
- Ability to cooperate
- No active ocular infection

### Exclusion Criteria

- Cataract
- Ocular trauma
- Strabismus
- Neurological diseases

### EyeQ System Architecture and AI Processing

The EyeQ system architecture consists of integrated layers designed to ensure maximum data processing speed and accuracy. The Data Acquisition Unit utilizes a digital camera to capture a raw video stream, focusing specifically on the Region of Interest (ROI)—the eyes and pupils [10]. The AI Processing Engine handles pre-processing by enhancing image quality and isolating visual noise. It then performs feature extraction for precise identification of pupil centers and angular computation to convert image coordinates into geometric angles representing the visual axes.

The computational core of the platform is architected using the TensorFlow framework. This deep-learning library provides the necessary infrastructure for training and deploying the neural networks responsible for precise ocular feature extraction and real-time gaze vector calculation, ensuring high-performance inference during physical movements [7,9]. For the backend infrastructure, data is transmitted via secure protocols (SSL/TLS) to a central application server that compares eye movements against Normative Data to classify the condition.

(As shown in Figure 1)

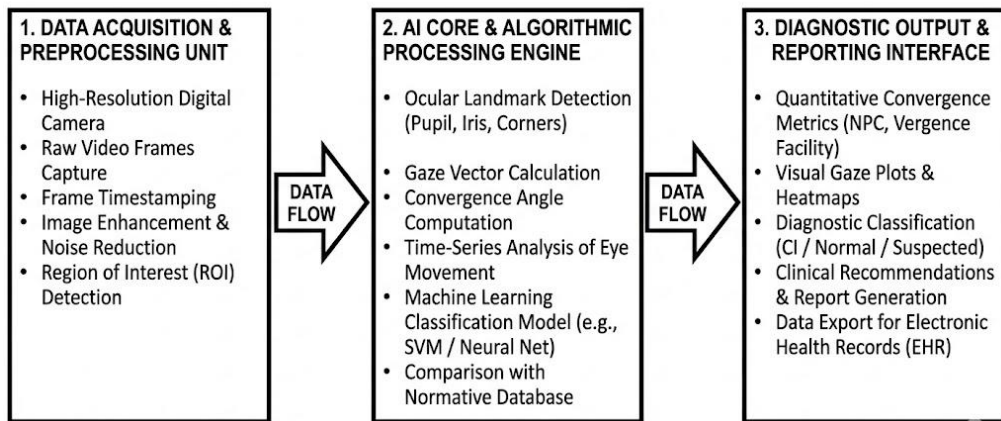


Figure 1. EyeQ System Architecture - Detailed Functional Flow

**Examination Protocol (Approach-Recede Mechanism)**

The platform utilizes an innovative examination protocol that mimics natural ocular responses in space, moving away from static visual stimuli.

**Approach Phase:** The user gradually brings the camera closer to their eyes. The algorithm monitors the effort of the extraocular muscles (Medial Rectus) and their ability to maintain the fixation point.

**Break Point Detection:** The AI identifies the exact moment of ocular axial deviation, which is the point where the brain fails to fuse the two images.

**Recede Phase:** As the user gradually moves the camera away, the system measures the Recovery Point, which is the distance at which the eyes regain their ability for correct alignment.

**Dynamic Analysis:** The system does not rely on distance alone; it analyzes the speed of response and fixation stability, providing a detailed assessment of Vergence Facility. The infrastructure routing is illustrated in Figure 2

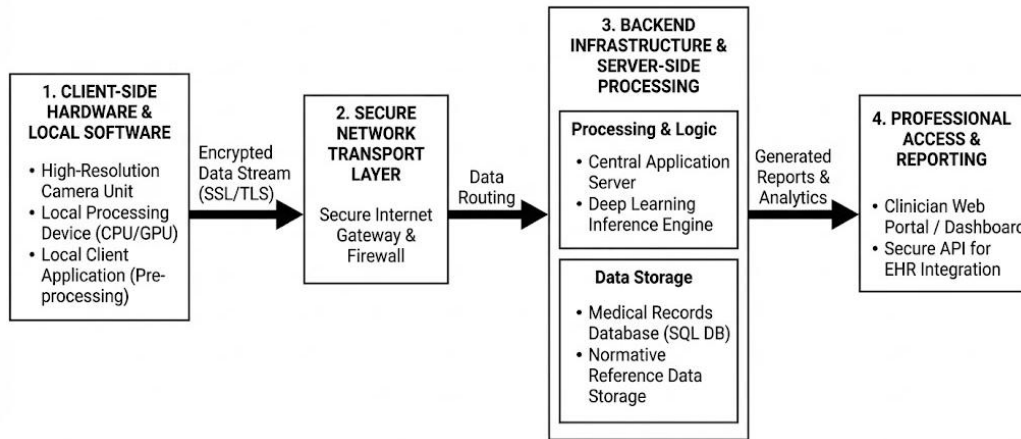


Figure 2. EyeQ System Infrastructure - Technical Architecture Diagram

### Comparison Protocol and Data Collection

The study's comparison protocol consisted of two distinct paths. Path A involved a traditional clinical manual examination performed by a certified optometrist. Path B involved an independent automated examination via the EyeQ platform. A dedicated software interface was used to record the platform's results and compare them with the manual medical report, focusing heavily on the accuracy of determining the Near Point of Convergence (NPC).

### Ethical Approval:

This study was conducted in accordance with the principles of the Declaration of Helsinki. The study received approval from the Institutional Research Ethics Committee of Al-Mustaqbal University, Iraq, (2025) prior to its commencement. All adult participants provided written informed consent. Written informed consent was also obtained from the parents or legal guardians of participants under the age of 18. All evaluated data were treated with the strictest confidentiality, and the privacy of participants was protected. Participation was voluntary, and participants were repeatedly informed that they could withdraw from the study at any time without any consequences. No procedures involving physical risk were performed on the participants, and the EyeQ platform was evaluated as an integrated, non-invasive diagnostic interface.

## Results

The clinical study was conducted on a sample of 50 participants to evaluate the diagnostic accuracy of the EyeQ platform. The study population comprised 32 males (64%) with ages ranging from 6 to 82 years, and 18 females (36%) with ages ranging from 16 to 52 years. The outputs of the EyeQ platform were analyzed and compared against the manual clinical diagnosis performed by a specialist. The platform demonstrated a highly reliable capability in identifying cases of convergence insufficiency, achieving an overall diagnostic accuracy of 94% (47 out of 50 cases). To provide a rigorous clinical validation, advanced statistical metrics including sensitivity, specificity, and Cohen's kappa coefficient (kappa) were calculated. The EyeQ platform demonstrated a diagnostic sensitivity of 95.2% and a specificity of 92.3%. Furthermore, the inter-rater reliability analysis between the automated AI system and the specialist's manual diagnosis yielded a Cohen's kappa coefficient of  $\kappa = 0.88$  ( $p < 0.001$ ), indicating an excellent and statistically significant level of agreement. The demographic characteristics and diagnostic outcomes are summarized in Table 1. The overall mean age of the clinical sample was  $34.6 \pm 12.4$  years

Table 1. Demographics and Diagnostic Performance of the EyeQ Platform

Characteristics & Outcomes	Frequency (n=50)	Percentage (%)
Gender & Age Distribution		
Male (Age range: 6 - 82 years)	32	64.0
Female (Age range: 16 - 52 years)	18	36.0
Diagnostic Performance		
Diagnostic Match (Accurate Detection)	47	94.0
Diagnostic Mismatch (Statistical Variance)	3	6.0
Cohen's $\kappa = 0.88$ (95% CI: 0.74–1.00, $p < 0.001$ )		

Statistical variance was recorded in only 3 cases (6%). A detailed clinical analysis of these discrepancies revealed that they were entirely attributed to physical ocular obstructions that hindered the AI's ability to accurately track the pupil. Specifically, 2 of the mismatched cases involved patients suffering from ptosis (drooping of the upper eyelid), while the remaining 1 case involved a patient with significant eyelid swelling

(edema). These physical barriers obscured the Region of Interest (ROI), thereby affecting the algorithmic feature extraction process.

## Discussion

The results confirm that the EyeQ platform possesses high reliability as a digital diagnostic tool. Achieving a 94% accuracy rate suggests that the Approach-Recede mechanism effectively identifies the Break Point and Recovery Point with a level of precision that demonstrated agreement comparable to conventional clinical assessment. [4,5]. A critical aspect of this study is the analysis of the specific discrepancies. While errors in eye-tracking might sometimes be attributed to inadequate ambient lighting or sudden oculomotor fatigue, our detailed clinical analysis of the three mismatched cases revealed they were entirely due to physical ocular obstructions (ptosis and severe eyelid edema). These anatomical barriers obscured the pupil, directly impacting the algorithmic feature extraction process. This highlights the necessity of a clear, unobstructed Region of Interest (ROI) to ensure peak accuracy.

Unlike manual clinical testing, the platform provides "Digital Objectivity". It eliminates the risk of subjective examiner bias and delivers quantitative data that can be used for longitudinal tracking of a patient's condition or response to vision therapy. Regarding the inclusion of a broad age demographic (6 to 82 years), which could conventionally introduce methodological confounding factors, the EyeQ platform implements an age-adaptive algorithmic framework to maintain diagnostic specificity. Prior to the examination, the user's chronological age is logged into the interface. For geriatric participants and older adults (over the age of 40), where presbyopia and age-related accommodative decline inherently confound traditional Near Point of Convergence (NPC) linear measurements, the AI processing core automatically shifts its diagnostic criteria. Instead of relying strictly on proximity-based NPC metrics, the algorithm dynamically monitors for ocular axial deviations—specifically identifying exodeviations or esodeviations. Because convergence decompensation in older cohorts primarily manifests as structural ocular alignment failure rather than isolated near-target accommodation tracking, this pre-programmed algorithmic pivot ensures high specificity and prevents age-related vision loss from yielding false-positive classifications. Similarly, for the youngest cohort (e.g., the 6-year-old participant), potential focus distractions were successfully managed via real-time frame filtering and

high-frequency pupil center validation to isolate deliberate vergence movements from brief saccadic tracking errors.

This framework combines eye-tracking technology with machine learning algorithms to quantitatively analyze movement, unlike traditional assessments that rely on subjective evaluation and examiner opinion [11, 12]. The EyeQ architecture uses real-time pupillary tracking and distance estimation to track the sequence of exotropia episodes while identifying the point of near convergence, eliminating the need for any subjective feedback from the subject during this process [13]. The system operates on a hybrid convolutional neural network and a bidirectional long-term memory architecture, analyzing the contrast between the two eyes and how gaze dynamics evolve, resulting in an efficient process unaffected by blinking or interruptions due to rapid eye movements [14, 15]. The platform extracts physiological features that determine the consistency of interocular coordination by capturing high-resolution, spatially continuous eye movements [16]. This process extracts biomarkers that allow for the objective classification of binocular vision performance, reducing the clinical gap between time-consuming manual examinations and data-driven diagnostic accuracy [17, 18]. Furthermore, the integration of synchronized movement patterns enables the system to derive reference standards for binocular vision integration, offering unique possibilities for early intervention [14, 13, 11] within a non-invasive telemedicine platform [9]. This architecture automates the characterization of visual pathways, overcoming the limitations of traditional clinical infrastructure that require manual coverage testing by trained personnel [20, 21]. Robust, automated, objective assessment methods can significantly improve the scalability of ocular misalignment diagnosis and reduce the inter-viewer variability in assessment often found in clinical practice [22, 23].

### Limitations

This study has some limitations that should be acknowledged. First, the sample size (n=50) is relatively small and confined to a specific demographic, which may limit the broader generalizability of the findings. Second, as observed in the clinical trials, the system's computer vision algorithms are highly sensitive to physical ocular obstructions. This currently limits the platform's application in patients with specific structural eyelid abnormalities, such as ptosis or severe edema. Future research should involve larger, multi-center clinical trials. Specifically, to definitively validate the

platform's efficacy as a national vision screening tool in Iraq, future collaborative studies must be conducted in coordination with local teaching hospitals and specialized medical centers, such as the Oncology and Hematology Center and Amir al-Mu'minin Hospital. Such strategic collaborations will facilitate the expansion of the screening sample size and allow for comprehensive clinical trials across broader and more diverse clinical demographics. Additionally, future technical iterations should explore the integration of infrared (IR) tracking sensors to overcome the aforementioned anatomical tracking barriers, multi-center clinical trials and potentially explore the integration of infrared (IR) tracking sensors to overcome these anatomical tracking barriers.

### Conclusion

The EyeQ platform represents a significant advancement in the integration of Artificial Intelligence within the field of optometry in Iraq. By successfully diagnosing 94% of convergence insufficiency cases with precision, this system shows promising potential for future large-scale screening applications. Such technology can significantly reduce diagnostic errors dependent on human subjectivity and provide a robust, standardized digital database for patient care and longitudinal monitoring.

### Patents and Intellectual Property

The system architecture, algorithmic framework, and the dynamic "Approach-Recede" examination protocol of the EyeQ platform are protected under registered intellectual property rights in Iraq. This registration establishes the platform as a proprietary national digital diagnostic asset for automated convergence insufficiency detection.

### Conflicts of Interest

The authors declared no conflict of interest.

### Data Availability Statement

The datasets generated and analyzed during the current study are not publicly available due to privacy and ethical restrictions regarding patient medical data, but are available from the corresponding author upon reasonable request.

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