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# Diagnostic Performance of the Offline Medios Artificial Intelligence for Glaucoma Detection in a Rural Tele-Ophthalmology Setting

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***Purpose:*** This study assesses the diagnostic efficacy of offline Medios Artificial Intelligence (AI) glaucoma software in a primary eye care setting, using nonmydriatic fundus images from Remidio's Fundus-on-Phone (FOP NM-10). Artificial intelligence results were compared with tele-ophthalmologists' diagnoses and with a glaucoma specialist's assessment for those participants referred to a tertiary eye care hospital.

***Design:*** Prospective cross-sectional study

***Participants:*** Three hundred three participants from 6 satellite vision centers of a tertiary eye hospital.

***Methods:*** At the vision center, participants underwent comprehensive eye evaluations, including clinical history, visual acuity measurement, slit lamp examination, intraocular pressure measurement, and fundus photography using the FOP NM-10 camera. Medios AI-Glaucoma software analyzed 42-degree disc-centric fundus images, categorizing them as normal, glaucoma, or suspect. Tele-ophthalmologists who were glaucoma fellows with a minimum of 3 years of ophthalmology and 1 year of glaucoma fellowship training, masked to artificial intelligence (AI) results, remotely diagnosed subjects based on the history and disc appearance. All participants labeled as disc suspects or glaucoma by AI or tele-ophthalmologists underwent further comprehensive glaucoma evaluation at the base hospital, including clinical examination, Humphrey visual field analysis, and OCT. Artificial intelligence and tele-ophthalmologist diagnoses were then compared with a glaucoma specialist's diagnosis.

***Main Outcome Measures:*** Sensitivity and specificity of Medios AI.

***Results:*** Out of 303 participants, 299 with at least one eye of sufficient image quality were included in the study. The remaining 4 participants did not have sufficient image quality in both eyes. Medios AI identified 39 participants (13%) with referable glaucoma. The AI exhibited a sensitivity of 0.91 (95% confidence interval [CI]: 0.71−0.99) and specificity of 0.93 (95% CI: 0.89−0.96) in detecting referable glaucoma (definite perimetric glaucoma) when compared to tele-ophthalmologist. The agreement between AI and the glaucoma specialist was 80.3%, surpassing the 55.3% agreement between the tele-ophthalmologist and the glaucoma specialist amongst those participants who were referred to the base hospital. Both AI and the tele-ophthalmologist relied on fundus photos for diagnoses, whereas the glaucoma specialist's assessments at the base hospital were aided by additional tools such as Humphrey visual field analysis and OCT. Furthermore, AI had fewer false positive referrals (2 out of 10) compared to the tele-ophthalmologist (9 out of 10).

***Conclusions:*** Medios offline AI exhibited promising sensitivity and specificity in detecting referable glaucoma from remote vision centers in southern India when compared with teleophthalmologists. It also demonstrated better agreement with glaucoma specialist's diagnosis for referable glaucoma participants.

***Financial Disclosure(s):*** Proprietary or commercial disclosure may be found in the Footnotes and Disclosures at the end of this article. *Ophthalmology Glaucoma 2024;■:1−9 © 2024 by the American Academy of Ophthalmology. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).*

*Supplemental material available at www.ophthalmologyglaucoma.org.*

Artificial intelligence (AI) has significantly impacted contemporary society, permeating every facet of human life. From self-driving automobiles to AI-guided robotic surgical procedures, the transformative influence of AI on our world is undeniable. Within the realm of health care, AI holds the potential to revolutionize telemedicine, rendering it more accessible, efficient, and proficient.[1,2]

Telemedicine has facilitated remote patient evaluations in the medical domain, yielding manifold advantages encompassing early disease detection, provisioning health care to



https://doi.org/10.1016/j.ogla.2024.09.002
ISSN 2589-4196/24

remote locales, minimizing patient travel, and diminishing health risks. In the domain of ophthalmology, telemedicine has proven to be a reasonably successful approach for vision care.[3,4] The utilization of portable handheld smartphone-linked nonmydriatic retinal cameras within telemedicine programs have demonstrated to be a practical method in the identification of sight-threatening ocular conditions such as diabetic retinopathy, age-related macular degeneration, retinopathy of prematurity, and glaucoma.[5−7] Nevertheless, the interpretation of images acquired through these cameras necessitates the expertise of trained manpower, and there is an acute shortage of trained eye care professionals worldwide, especially in rural communities and less-developed nations. This is where AI may emerge as an asset, discerning eye diseases from fundus images.[8−10]

One such condition amenable to AI-aided fundus image screening may be glaucoma. Glaucoma, a chronic ocular disorder capable of inducing irreversible visual impairment if not timely diagnosed and managed, is a global public health challenge, particularly in the developing world.[11,12] The leading global causes of blindness in those aged ≥ 50 years in 2020 were cataract (15.2 million cases [9% uncertainty interval {UI} 12.7%−18.0%]), followed by glaucoma (3.6 million cases [UI: 2.8%−4.4%])[13] The fact that glaucoma usually presents with no symptoms until it reaches an advanced stage emphasizes the critical importance of early identification and intervention. In the developing world, over 90% of glaucoma cases go undetected within the community, with > 50% reaching an advanced stage and nearly 20% experiencing blindness at the time of diagnosis.[14−20]

Vision Centers (VC) at the Aravind Eye Care System are primary eye care centers that offer in-person examinations by a vision technician and further synchronous teleconsultation with an ophthalmologist at the base hospital. The facilities available at VC include refraction, slit lamp evaluation, intraocular pressure (IOP) measurement, and fundus imaging.[21] Artificial intelligence algorithms hinge on deep convolutional neural networks to identify (classify) ocular conditions from retinal images. The functioning of deep convolutional neural networks necessitates substantial computational capabilities at the user end or relies on cloud-based processors, mandating image uploads to cloud platforms. However, telemedicine initiatives often target rural areas with limited computational resources and internet connectivity[2,4] This study evaluates an offline AI system (Medios Glaucoma AI) [22] engineered to operate on a smartphone-linked nonmydriatic fundus camera (Remidio's FOP NM-10- Fundus On Phone Non-Mydriatic), enabling the detection of glaucoma from retinal images at VC (on-the-edge), even in resource-constrained settings without dependency of the internet.

## Methods

In this prospective cross-sectional study, our objective was to evaluate the diagnostic efficacy of an offline AI system integrated into a nonmydriatic fundus camera designed for smartphone use in glaucoma screening. This evaluation was carried out within the context of our VC model, which involved assessing subjects suspected of having glaucoma and referring them to a base hospital for glaucoma assessment. The study was conducted at 6 VCs, which serve semirural and rural communities as their permanent primary eye care facilities. The study was approved by Institutional Ethics Committee of Aravind Eye Hospital, Pondicherry, and adhered to the tenets of declaration of Helsinki (Ethics approval number: AEH-PDY/EC/OA/108/2021, The Clinical Trials Registry-India registration number is REF/2021/07/045 014).

Operated by allied ophthalmic personnel, these VCs facilitate telemedicine-based consultations between patients and ophthalmologists at the base hospital, enabling access to further care. The technicians at VCs are well trained mid-level ophthalmic personnel with approximately 5 years of experience. They were trained at the base hospital before becoming in charge of the VCs. They had been using nonmydriatic fundus cameras for > 2 years (AI was a new addition to these fundus cameras). To screen for glaucoma, the allied ophthalmic personnel utilized Remidio's FOP NM-10 nonmydriatic fundus camera equipped with built-in Medios AI. After image acquisition users can initiate the AI analysis directly on the device to obtain the diagnosis. This eliminates the need to transfer images from the fundus camera to a separate computer for AI analysis or for a cloud-based inferencing. This study was conducted in 6 satellite VCs, attached to Aravind Eye Hosptial, Pondicherry, encompassing a diverse patient population.

### Inclusion and Exclusion Criteria

Consecutive participants > 18 years of age who provided informed written consent and were willing to spend extra time for fundus photography were included from 6 VCs between December 30, 2021, and March 31, 2022. Exclusion criteria encompassed individuals with acute vision loss, narrow angles preventing safe dilation, coexisting ocular pathologies, significant media opacity, or any other factors that would impede participation.

### Study Device

The FOP-NM 10 (Remidio Innovative Solutions Pvt Ltd, India) is a portable nonmydriatic fundus camera, equipped with a 42-degree field of view. Weighing 1.1 kg, the device can be conveniently mounted on a chin rest or used handheld and can capture fundus images with its auto capture feature. The FOP NM-10 incorporates the Medios Glaucoma AI, which operates offline, on-the-edge and delivers examination reports nearly instantaneous.[22,23] These reports encompass vertical cup-to-disc ratio and activation maps highlighting areas of abnormality that triggered a diagnosis by the AI. Figure 1 depicts the AI output for 3 subjects: one with no referable glaucoma, a subject with a suspicious disc referred for further evaluation, and a patient with probable glaucoma (reported as referable glaucoma) for further glaucoma evaluation.

## Clinical Evaluation

### VC Clinical Evaluation

Subjects visiting the VC for a glaucoma evaluation, or a general eye check-up underwent comprehensive evaluations. This included the following: obtaining a clinical history, best-corrected visual acuity, slit lamp examination, Goldmann Applanation Tonometry, and fundus photograph by an allied ophthalmic personnel. Gonioscopy was not done as a part of evaluation. Fundus images were captured using the FOP NM-10 according to a specific protocol as follows.

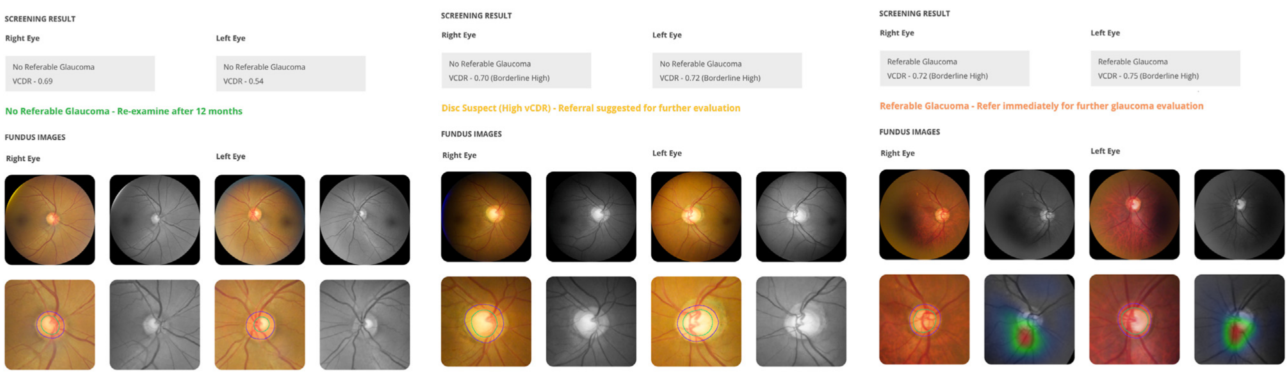


**Figure 1.** Illustration depicting a Medios Glaucoma AI report showcasing the AI output for 3 subjects: those without referable glaucoma, a disc suspect referred for further evaluation, and a patient with referable glaucoma promptly referred for additional glaucoma assessment. The color fundus images displayed in the top row were captured using the Remidio FOP NM-10 fundus camera. The Medios AI automatically identifies and crops the optic nerve head region, while the cup and disc margins are delineated by the AI, as depicted in the bottom row. Heat maps highlighting possible areas of structural changes on the red-free images are generated automatically by the AI for positive cases. AI = artificial intelligence; vCDR = vertical cup-to-disc ratio.

## Imaging Protocol and Medios AI Output

A single disc-centered 42-degree image per eye was captured using the FOP NM-10 by the allied ophthalmic personnel at the VC who had a minimum 5 years' of experience in handling ophthalmic devices. Subsequently, the images were submitted to AI within the camera system for analysis. The development and working details of Medios AI-Glaucoma have been described elsewhere.[23] The AI software assessed these images for both quality, vertical cup-to-disc ratio and other structural optic nerve head (ONH) changes like notching and nerve fiber layer defects. In instances where image quality was deemed insufficient, the operator attempted up to 2 additional captures. If these attempts were unsuccessful, pupils were dilated, and the process was repeated (Figure 2).

## Tele-Ophthalmology Diagnosis at Tertiary Center

The captured Fundus-on-phone (FOP) images were transmitted to the base hospital using a cloud platform for remote diagnosis. Fellowship trained tele-ophthalmologists who were glaucoma fellows with a minimum of 3 years of ophthalmology and 1 year of glaucoma training experience, assessed the FOP images. This evaluation was performed in a masked manner, with the ophthalmologist being unaware of the AI diagnosis as well as the IOP. Subsequently, based on pre-defined criteria (Appendix 1.2), the ophthalmologist categorized the cases into 3 groups: those with perceived definite glaucomatous changes, of glaucoma suspects, and those with no glaucoma (Fig 2). Because VCs did not have perimetry capabilities, the tele-ophthalmologist made a diagnosis based only on fundus photos, and no other diagnostic tests were used to aid the diagnosis of glaucoma.

## Referral to Base Hospital

Individuals identified as having either referable glaucoma or a disc suspect by either the AI system or by tele-ophthalmologist were referred to the base hospital for comprehensive glaucoma assessment by a glaucoma consultant who has more than 10 years of experience in providing glaucoma care (S.U.). Those identified as normal by either the AI system or by tele-ophthalmologist were not referred. This evaluation encompassed a thorough clinical evaluation including slit lamp examination, Goldmann Applanation Tonometry, gonioscopy, and fundus evaluation using slit lamp biomicroscope with a 90D lens. Additionally, visual field (VF) examinations using Humphery Visual Field Analyzer (HFA II-i, Carl Zeiss Meditec) Swedish interactive thresholding algorithm (SITA) standard strategy and a 24-2 and or 10-2 programme as deemed necessary, ONH and retinal nerve fiber layer (RNFL) analysis using OCT (Cirrus HD-OCT 5000, Carl Zeiss Meditec) were performed. All individuals were required to have a reliable VF report (false positive, false negative, and fixation losses $< 33\%$) for diagnosis. If not, the participants were reinstructed, and the VF test was repeated after a short break. The final diagnosis at the base hospital, in accordance with predetermined criteria (see Appendix 1.1), was made by a glaucoma specialist (S.U.) who was masked to patient referral status from the VC.

## Sample Size

The study design involved the inclusion of a minimum of 200 participants to identify discrepancies in the diagnosis of referable glaucoma between the AI system and glaucoma specialists. This calculation considered a range of potential true discordance rates from 10% to 50%, while maintaining a minimum sensitivity of 80%. To ensure comprehensive representation across the 3 categories, namely glaucoma, disc suspects, and no glaucoma, a total of 250 participants were targeted. This figure accounted for potential dropout instances due to issues related to image quality.

## Statistical Analysis

All the data were entered into Microsoft Excel. A 2*2 confusion matrix was used to compute the sensitivity and specificity of the AI system against the tele-ophthalmologist diagnosis. Additional metrics included the positive

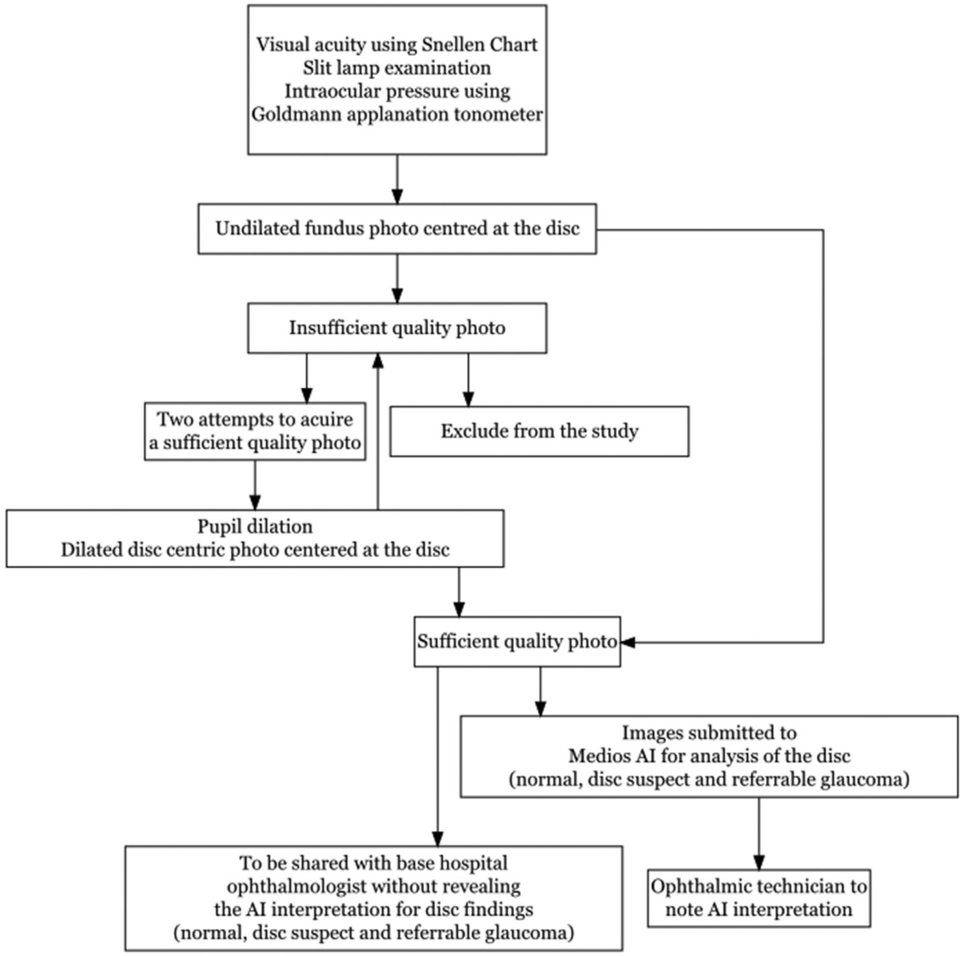


**Figure 2.** Study methodology flowchart. AI = artificial intelligence.

predictive value and the negative predictive value along with Wilson 95% confidence intervals were calculated. Cohen kappa coefficient was calculated between AI diagnoses and tele-ophthalmologist diagnoses. R statistical software was used for statistical analysis.

## Results

A total of 303 participants underwent screening as per protocol. Among the 303 participants, 299 (98.6%) met the AI's and tele-ophthalmologist satisfactory image criteria for either one or both eyes. Among these 299 participants, 274 (91.6%) subjects had sufficient image quality in both eyes, while 25 (8.3%) subjects had adequate image quality in only one eye. Subsequent analysis was conducted on eyes with adequate image quality on these 299 participants. Referrals were made at the patient level; one of the eyes had to meet the referral criteria (referable glaucoma or disc suspect) to be referred to the base hospital. In order not to miss any underlying pathology, patients with ungradable images (one or both eyes) were automatically referred to the base hospital. All analysis in this study were conducted at the patient level similar to other screening solutions.[24–26] There were 156 women and 143 men. The mean age was 45 ± 14.4 years. Among the participants, 46 (15.3%) had a history of diabetes, and 4 (1.3%) had a history of hypertension. Because cataract and glaucoma are both age-related conditions, 133 participants (44.4%) required dilation for clear fundus image due to cataractous changes.

Medios AI identified 39 participants (13%) as referable glaucoma, whereas tele-ophthalmologists diagnosed 22 (7.3%) eyes as referable glaucoma (refer to Fig 3); 84.6% (253 participants) of AI diagnoses agreed with tele-ophthalmologists' diagnoses. Figure 4 shows Standards for Reporting Diagnostic accuracy studies (STARD) flowchart outlining the diagnoses made by Medios AI and tele-ophthalmologist for the 3 categories (normal, disc suspects, and referable glaucoma).

We assessed the performance of Medios AI using both liberal and conservative criteria. Under the liberal criterion, we combined participants with disc suspect and glaucoma diagnoses into a single "referable glaucoma group," while under the conservative criterion, we combined the normal and disc suspect into a single "normal group." The contingency table depicting the comparison between tele-ophthalmologist and Medios AI under both liberal and conservative criteria is presented in Tables 1 and Table 2 shows the sensitivity, specificity, positive predictive values, and negative predictive values.

The Cohen's kappa coefficient was calculated for the 3 categories (normal, disc suspects, and referable glaucoma) classification, as well as for the binary liberal and conservative criteria

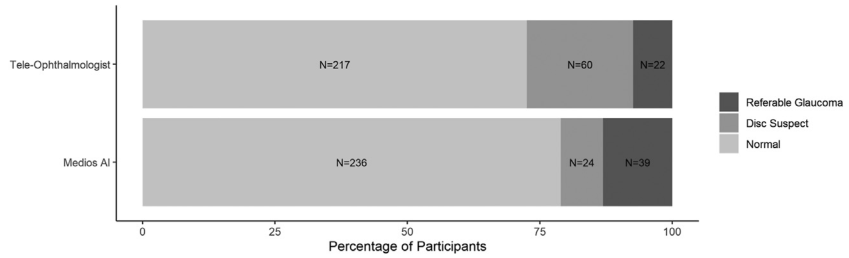


**Figure 3.** Percentage of participants identified as normal, disc suspect and referable glaucoma by Medios AI and tele-ophthalmologist. N = number of participants. AI = artificial intelligence.

classification. Table 3 displays the Cohen kappa coefficient between AI diagnosis and tele-ophthalmologist diagnosis. As shown, the Cohen kappa values were > 0.60 for all different criteria, indicating substantial agreement between AI and tele-ophthalmologist.

## Referrals to Base Hospital (Tertiary Care)

Out of 299 individuals screened at vision centers, 85 individuals identified as having referable glaucoma or disc suspect either by the AI system or by tele-ophthalmologist were referred to the base hospital. Out of which, 57 visited the base hospital. One participant's data were excluded from the base hospital analysis due to a non-glaucomatous pale disc (which was picked up as disc suspect by AI), leaving the data of the remaining 56 participants for analysis. At the base hospital, all subjects underwent comprehensive eye examination including fundus evaluation using slit lamp biomicroscopy with 90D lens, VF examination and OCT. The glaucoma specialist at the base hospital made a final diagnosis based on all available tests. The key difference between the diagnoses made by the tele-ophthalmologist and the glaucoma specialist at the base hospital was that the tele-ophthalmologist made their diagnosis solely based on fundus photos, whereas the glaucoma specialist made a diagnosis based on all available diagnostic test results.

Figure 5 presents the diagnoses made by the AI, tele-ophthalmologist, and glaucoma specialist. As seen, the agreement between AI-aided diagnosis and the glaucoma specialist was 80.3%, which is better than the agreement between the glaucoma specialist and the tele-ophthalmologist (55.3%). The agreement between AI-aided diagnosis and the tele-ophthalmologist was 42.8%.

## Discussion

In this study, we evaluated the diagnostic performance of an offline AI-based diagnostic system compared to that of synchronous teleophthalmolgist's ability to diagnose

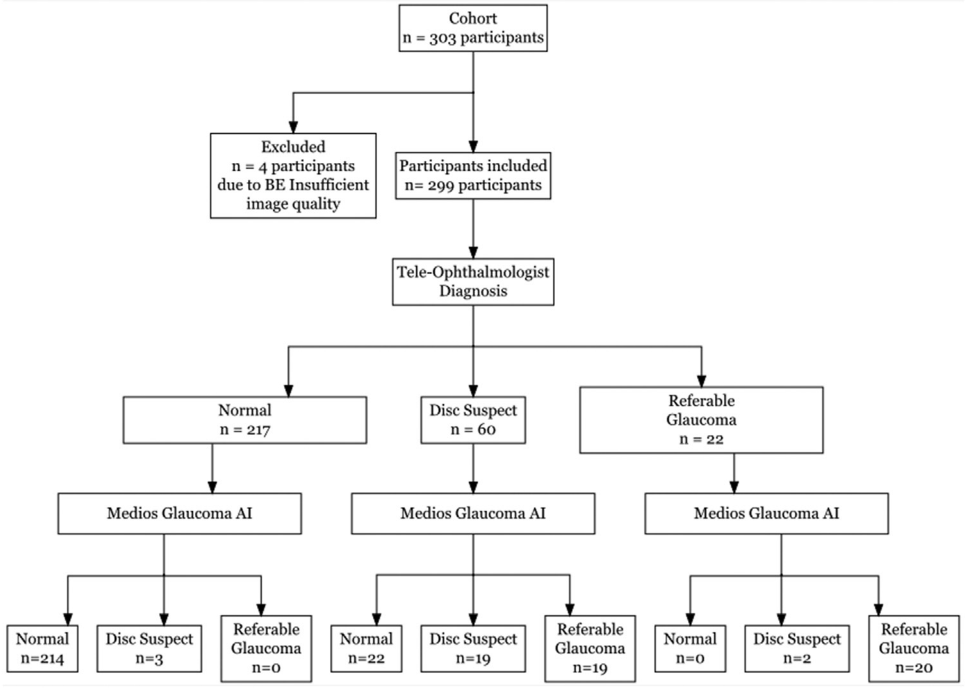


**Figure 4.** STARD flowchart. AI output against tele-ophthalmologist diagnosis. AI = artificial intelligence, BE = both eyes.

Table 1. Contingency Table Showing Tele-Ophthalmologist and Medios AI Diagnosis for Both Liberal and Conservative Criteria

| Tele-Ophthalmologist<br>Medios AI | Liberal Criterion (Disc Suspect and Referable Glaucoma as 1 Group) | | | Conservative Criterion (Normal and Disc Suspect as 1 Group) | | |
|---|---|---|---|---|---|---|
| | Referable Glaucoma | Normal | Total | Referable Glaucoma | Normal | Total |
| Referable glaucoma | 60 | 3 | 63 | 20 | 19 | 39 |
| Normal | 22 | 214 | 236 | 2 | 258 | 260 |
| Total | 82 | 217 | 299 | 22 | 277 | 299 |

glaucoma. We highlight the dual potential of AI technology: first, to enhance clinical decision-making in the tele-ophthalmology, and, second, to extend healthcare access to those communities in urgent need. With an ever-increasing older population, improved life expectancy, limited trained manpower, a huge upsurge in demand for eye care services is expected in the near future, and we believe that having a reliable AI to screen for early glaucoma can help clinicians and the community in a big way.

The AI's diagnoses demonstrated a relatively good concordance rate when compared to assessments by tele-ophthalmologists (kappa coefficient = 0.61) and an even better with glaucoma specialists (kappa coefficient = 0.76). The liberal criteria yielded a sensitivity of 0.73, and the specificity was 0.99. Similarly, the conservative criterion showed a sensitivity of 0.91 and specificity of 0.93 (Table 3).

We identified a group of participants as referable glaucoma or glaucoma suspects based on their disc appearance and this group was referred to the base hospital for further evaluation. Figure 5 illustrates the agreement between AI, tele-ophthalmologist, and the glaucoma specialist. It is evident that the percentage of agreement is higher between the glaucoma specialist and AI-aided diagnosis (80.3% agreement) compared with the agreement between the tele-ophthalmologist and the glaucoma specialist (55.3% agreement). AI had a lower number of false positive referrals compared to the tele-ophthalmologist. Specifically, AI categorized only 2 out of 10 nonglaucomatous cases as suspects (Fig 5), whereas the tele-ophthalmologist categorized 9 out of 10 normal cases as glaucoma suspects. Additionally, AI performed better in terms of identifying glaucoma cases, only 1 out of 28 definite glaucoma cases as suspects (Fig 5). In contrast, the tele-ophthalmologist identified 13 out of 28 glaucoma cases as normal or suspects, differing from the glaucoma specialist's assessment when the specialist had the advantage of OCT, VF, and IOP data. The tele-ophthalmologist had a better agreement with the glaucoma specialist when identifying disc suspects. Only 3 out of 18 disc suspects were identified as either normal or glaucoma by the tele-ophthalmologists, whereas AI misclassified 8 out of the 18 participants, identifying 4 of them as glaucoma and 4 as normal. Subjects categorized as glaucoma suspects based on the optic nerve head appearance present a challenge even for experts, as this group often falls into a gray area. It is required to monitor disc suspects over time to determine if there is true progression to glaucoma. From a public health standpoint, the likelihood of rapid progression leading to a lifetime blindness is minimal in this group.[27–30]

As previously mentioned, the agreement between tele-ophthalmologists and glaucoma specialists was lower compared to the agreement between AI and glaucoma specialists. Tele-ophthalmologists were trained to diagnose structural optic disc changes in glaucoma. Although the glaucoma specialists at the base hospital did have more experience (> 10 years in glaucoma practice), we believe the lack of agreement between tele-ophthalmologists and the glaucoma specialist was primarily due to the availability of additional diagnostic tests (gonioscopy, perimetry, and OCT). This is supported by prior studies where optic disc examination alone by glaucoma specialists (with over 7 years of experience in glaucoma care) resulted in an underestimation of definite glaucoma cases (60% of glaucoma cases on image grading compared to a 94% on comprehensive evaluation by the same set of specialists).[31]

It is also important to note that the glaucoma specialist in our study based their diagnosis not only on optic disc photos but also on additional tests such as IOP, gonioscopy, clinical examination, VF, and OCT. Remarkably, AI achieved promising results when compared with the glaucoma specialist despite being challenged with fundus images alone without the need for additional tests. Artificial intelligence consistently recognized definite glaucoma cases with more certainty than the tele-ophthalmologist when presented with the same images It can also aid to improve the diagnostic consistency of postgraduate ophthalmologist trainees or glaucoma fellows as well as comprehensive ophthalmologists, which is of paramount importance in academic institutes involved in training.

Table 2. Showing Sensitivity, Specificity, Positive Predictive Value, and Negative Predictive Medios AI for Both Liberal and Conservative Criteria

| | **Liberal Criterion (Disc Suspect and Referable Glaucoma as 1 Group)** | **Conservative Criterion (Normal and Disc Suspect as 1 Group)** |
|---|---|---|
| Sensitivity | 0.73 (0.62–0.82) | 0.91 (0.71–0.99) |
| Specificity | 0.99 (0.96–1.00) | 0.93 (0.89–0.96) |
| Positive predictive value | 0.95 (0.87–0.99) | 0.51 (0.35–0.68) |
| Negative predictive value | 0.91 (0.86–0.94) | 0.99 (0.97–1.00) |

Table 3. Cohen's Kappa Coefficient between AI and Tele-Ophthalmologist for the 3 Categories (Normal, Disc Suspects, and Glaucoma) Classification, as Well as for the Binary Liberal and Conservative Criteria Classification

| Criteria | Kappa |
|---|---|
| Three categories classification | 0.61 |
| Liberal criteria | 0.77 |
| Conservative criteria | 0.62 |

Fundus photographs are considered suitable for population-based glaucoma screening [32,33] because of their simplicity, cost-effectiveness, and potential to identify cases. Handheld fundus cameras are affordable and approximately 50% to 60% lower cost compared to the tabletop models. Recent technology has integrated smart phones into fundus photography and have shown promising results to detect sight-threatening eye diseases such as glaucoma and diabetic retinopathy [34–36] Artificial intelligence strategies have extensively utilized fundus photos to detect sight-threatening eye diseases and have shown its capability to serve as a reliable tool in assisting clinicians.[32,37–48] Artificial intelligence also appears to have potential to mitigate inter-observer variability, a common challenge in ophthalmology diagnostics, especially glaucoma.

Offline AI, on-the-edge also offers a significant advantage, as it can be used in resource-constrained areas where internet connectivity is poor. This efficiency could lead to improved patient referrals in community and rural screening setups and enable timely interventions for patients with potentially sight-threatening conditions.

One of the limitations of our study is that 44.4% (i.e., around 133 participants required dilation to obtain clear fundus image). This necessity stems from the coexistence of age-related conditions such as glaucoma and cataracts coupled with small pupil size (< 3 mm), which require dilation to capture an adequate quality fundus photo. Therefore, it is not ideal for patients with concurrent narrow angles with media opacity.

The average age of participants in our study was $45 \pm 14.4$ years. However, the mean age for participants diagnosed as disc suspect and glaucoma was notably higher, at 55.56 (standard deviation [SD] = 13.94), whereas the mean age for those classified as normal was 42.01 (SD = 13.33). It is important to note that the inclusion of normal participants influenced the overall average age observed in our study. Another limitation is that those referred to the base hospital were disc suspects and glaucoma patients. We did not evaluate the performance of AI on those identified as normal at the VC. Hence, the evaluation of the specificity of AI against glaucoma specialists is limited.

An important strength of this study is that we evaluated AI as a screening tool at rural community-based vision centers, where the need to detect sight-threatening eye diseases like glaucoma is crucial. Our study has revealed that the AI system exhibits a reasonably strong ability to detect referrable glaucoma using structural information available on fundus images. Integrating an offline AI system with fundus photography eliminates the need and cost associated with transmitting these images over the internet to tele-ophthalmologists for diagnosis. This efficiency could lead to improved patient referrals in community and rural screening setups and enable timely interventions for patients with potentially sight-threatening conditions. Artificial intelligence has also shown a decrease in false positive referrals, thereby reducing the patients need to visit the hospital, saving patients travel expenses and further testing costs, minimizing the unwanted mental stress associated with false positive diagnoses, and optimizing the utilization of resources, including staff for testing all false positive patients in. The future AI development should aim to integrate a single AI system capable of detecting multiple sight-threatening eye diseases, such as diabetic retinopathy, glaucoma, age-related macular degeneration, and more. Our team has already laid the groundwork for this approach that has shown potential for an effective screening strategy for glaucoma.[23,49–51]

In conclusion, this study highlights the promising role of offline Medios AI in glaucoma diagnosis. Collaborative utilization of AI alongside clinical expertise has the potential to revolutionize community screening and ophthalmological practice, ultimately leading to improved patient outcomes and more efficient healthcare delivery. Artificial intelligence aided diagnosis exhibited a higher level of agreement with the glaucoma specialist, who had access to a battery of diagnostic tests, compared to tele-ophthalmologists, who relied solely on fundus images. Although AI technology demonstrated accuracy, consistency, and diagnostic efficiency, its limitations, privacy, and ethical considerations should be carefully considered.

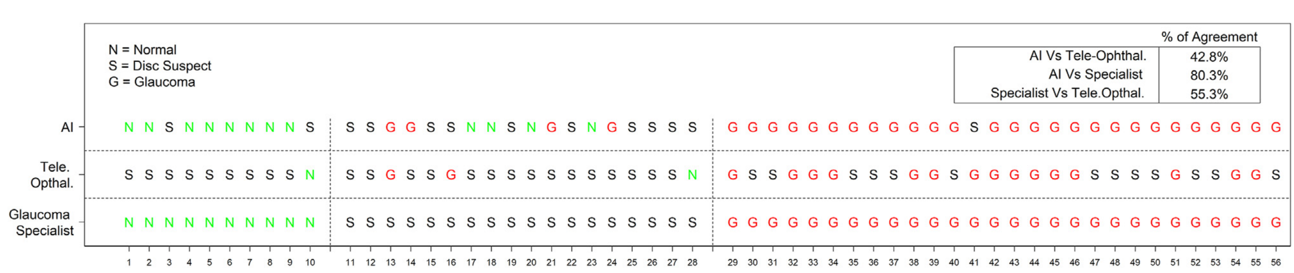


**Figure 5.** Figure displaying the individual diagnoses provided by the glaucoma specialist, tele-ophthalmologist, and the AI for each participant. AI = artificial intelligence.

## Footnotes and Disclosures

Originally received: January 22, 2024.
Final revision: August 31, 2024.
Accepted: September 9, 2024.
Available online: ■■■. Manuscript no. OGLA-D-24-00024.

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A portion of the data was presented at the 33rd American Glaucoma Society (AGS) Annual Meeting held in March 2023 in Austin, TX.

Disclosures:

All authors have completed and submitted the ICMJE disclosures form.

The authors have made the following disclosures:

D.P.R.: Employee − Remidio Innovative Solutions Inc.

S.B.G., K.N., and S.B.: Employee - Remidio Innovative Solutions Private Limited.

F.M.S.: Patents − Patents under Remidio Innovative Solutions and Medios Technologies (subsidiary of Remidio) including a patent covering the software described in this publication; Shares − Remidio Innovative Solutions; Employee −Medios Technologies (subsidiary of Remidio).

Financial Support was provided by Aravind Eye Hospital, India and Remidio Innovative Solutions, India.

HUMAN SUBJECTS: Human subjects were used in this study. The study was approved by Institutional Ethics Committee of Aravind Eye Hospital, Pondicherry Ethics Committee and adhered to the tenets of declaration of Helsinki. Participants above 18 years of age who provided informed written consent were included from 6 VCs.

Author Contributions:

Conception and design: Upadhyaya, Rao, Negiloni, Venkatesh

Data collection: Upadhyaya, Kavitha, Bhandary

Analysis and interpretation: Ballae Ganeshrao, Negiloni

Obtained funding: N/A

Overall responsibility: Upadhyaya, Rao, Kavitha, Ballae Ganeshrao, Negiloni, Savoy, Venkatesh

Abbreviations and Acronyms:

**AI** = artificial intelligence; **CI** = confidence interval; **IOP** = intraocular eye pressure; **VF** = visual field.

Keywords:

AI, Glaucoma, Screening, Tele-ophthalmology, Vision centers.

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