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A Mobile-Based Decision Support Tool for Preliminary Eye Anomaly Detection in Community Health Practice

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Abstract

It has been predicted that about 2.2 billion people globally have visual impairment, where half of these cases remain preventable or treatable in resource-constrained regions. Existing mobile health(mHealth) tools are fragmented. They focus on isolated diagnostic functions and require constant internet connectivity. This study presents an integrated, offline-capable mobile decision support tool that combines Snellen visual acuity, Ishihara color, and symptom-based AI analysis into a single application. The proposed tools used the Flutter framework and TensorFlow Lite and utilize a Convolutional Neural Network for on-device inference. These ensure data privacy and functionality in remote areas. A curated dataset of 1,200 clinical records from three different hospitals was used for model development with a pilot evaluation with 50 participants was conducted to validate performance. The study's diagnostic results show a high accuracy of 94%, with a precision of 95.6%, recall of 91.7%, and an F1-score of 93.6%. The Benchmark against existing solutions (Peek Acuity and IDx-DR) illustrates the proposed system's unique multi-modal capabilities and low-cost accessibility. The proposed study application for the community health workers is to bridge the gap between preliminary screening and clinical referral. These offer a scalable solution for eye care in low-resource settings.

1.0 Introduction

Visual impairment remains one of the health challenges globally. of the 2.2 billion affected cases being preventable or treatable [1,2]. The Snellen chart is clinically fundamental but faces accessibility limitations in resource-poor settings. Digital adaptations now demonstrate 98% agreement with traditional charts when properly implemented [3,23]. These offer automated calibration and remote testing capabilities [4,5]. A sub-division of Artificial Intelligence, machine learning algorithms, can identify diabetic retinopathy by comparing retinal images to 94-99% accuracy. These reveal how eye diseases have been detected better through artificial intelligence [6,7]. The human eye is a complex body organ used as a sensor that has an advanced refraction technique of light from the cornea, through the pupils controlled by the iris, and the lens, then into the retina where data is processed through the neurosystem [1]. Some of the ocular pathologies that are common in the whole world are: There is cataract, in which the lens of the eye becomes opaque [8,9]. Then there is Glaucoma, which affects the optic nerves of the eye due to increased pressure [10,11]. Moving on, there is Diabetic Retinal Damage, in which the retina of the eye meets damaged capillaries [12,13]. Similarly, AMD brings about degeneration in the retina of the eye [14], and finally, there are Refractive Errors [15]. Evidence supporting preventive measures includes the 20-20-20 Rule in relation to digital eye strain [16,17,21]. Along with this, there is the Nutritional Approach in association with AMD [14,22]. Similarly, there is Applying Warm Compress in association with dry eye symptoms [4,18] and finally, UV Glasses are potentially useful in preserving vision in the retina of the eye.

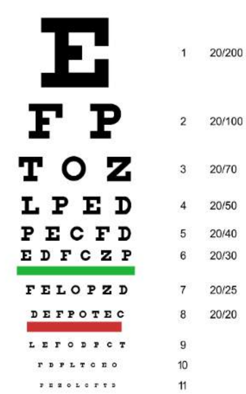

Figure 1.1 Snellen Chart [28].

The Snellen chart exposes the parameter chart in Figure 1.1, which depicts the average height of the letters, the thickness of the strokes, and the distance that defines every line. The rows are made in such a manner that the entire letter measures 5 arc-minutes at the specified distance, the strokes and gaps measure 1 arc-minute, respectively. The main contributions in this research are:

1. The development of a proposed offline-first mobile architecture using Flutter and TFLite.
2. Integration of five distinct screening modules into a single decision-support application workflow.
3. A pilot-validated dataset curated by ophthalmologists specifically for community health contexts.

This study is structured into five sections. The introduction outlines the global impact of visual impairment and the research objectives. The literature review identifies gaps in existing mHealth tools, particularly in multi-modal integration and offline use. The methodology describes the design science approach, Flutter application development, and on-device CNN implementation. The results and discussion provide evaluation metrics of the pilots and comparisons based on Peek Acuity and IDx-DR results. The study provides concluding points, limitations, and future improvement recommendations.

The current eye screening tools that are mobile in nature show prospective potential. There are severe constraints on these tools. Bastawrous et al. created Peek Acuity, where a smartphone test of visual acuity was evaluated (98% interchangeable with Snellen charts), though not modified by disease-specific AI. Ting *et al.* demonstrated 94% raying of diabetic retinopathy with CNNs, which were processed on the cloud, allowing it to be used offline [19]. Bhaskaran et al provided a portable fundus camera that detects cataracts (91% accuracy) but relies on hardware of specialist caliber. [15]. provided AI-based refractive error prediction through mobile applications (87% accuracy), but not dynamic vision measurements. [7, 18]. The study was the first retinal analyzer to operate offline (FDA-approved IDx-DR), but the cost was too high to scale it. Interoperability lapses in the tools that combine acuity with pathology detection were pointed out by Keel et al [24], and the failure to meet the affordability criteria of the WHO by 68% of the tools was highlighted [4]. Together, these studies show a longstanding gap between the accuracy of diagnosis, its availability, and its multifunctionality, a gap that is filled in this study by means of integrated, offline-capable decision support.

Nevertheless, the existing solutions are still split some of them are dedicated to the analysis of static images, others to individual tests of acuity, without a combination of functional vision evaluation with artificial intelligence diagnostics [24,27].

The currently available mHealth technology and ML tools used for eye care are scattered, focusing only on specific applications, including retinal imaging and acuity testing [3,6].

The limitations are: Specialization Bias [20,26] Internet Dependence [7], Lack of Multimodal Assessment [24,25]. The research aims to fill this gap by creating an offline-compatible mobile app that entails anisocoria, color vision, and symptomicism in an integrated manner.

To address these gaps, this study explores the following:

1. **RQ1:** Can an integrated mobile system achieve high diagnostic concordance with clinical gold standards in an offline environment?
2. **RQ2:** To what extent does the integration of multi-modal data (acuity, color, and symptoms) improve the preliminary detection of anomalies?
3. **RQ3:** What are the technical requirements to ensure reliable AI inference on low-specification mobile hardware?

2.0 Materials and Methods

This study employs a design science and experimental research approach to develop and evaluate a mobile-based decision-support system for preliminary eye anomaly detection in community health settings. The methodology integrates four key components:

1. Data collection and Annotation
2. Machine learning model Implementation
3. System design
4. Pilot-based evaluation, which requires both technical precision and usability.

The architecture includes an offline-friendly, modular Client-Server model suitable for low-latency use. The system is different from other available tools that use cloud computing and/or API calls (e.g., [6]) since this system utilizes the TensorFlow Lite engine (.tflite) inside the Flutter frontend.

It has the following benefits:

1. Data Privacy: Patient data remains on the device and is compliant with HIPAA standards.
2. Zero Latency: It eliminates latency since the results require no internet connection.

3. Resource Efficiency: It is achieved with the help of the Dart-based scoring algorithm, which runs on the device and consumes less battery on mid-range mobile devices.

Data Collection & Annotation

A stratified dataset consisting of 1,200 records was curated via:

1. **Clinical Collaboration**: Three ophthalmologists from Nigerian hospitals (Ade Vision, State Hospital Asubiaro, UNIOSUN Teaching Hospital) reviewed the records
   - 800 Snellen test results (6/6 to 6/60 scale)
   - 200 Ishihara plate responses
   - 200 symptom surveys (20 item Likert-scale questionnaire)
2. **Quality Control**: Inter-rater reliability, Cohen's Kappa (κ) to ensure annotation consistency. $\kappa = \frac{p_o - p_e}{1 - p_e}$ Where p_o is the observed agreement and p_e is the hypothetical probability of chance agreement. The study achieved a $\kappa = 0.82$, indicating "strong" agreement.

The dataset is intentionally limited in size and is explicitly framed as a pilot-scale dataset suitable for preliminary model validation rather than large-scale clinical deployment.

Machine Learning Model Implementation

The machine learning model was developed using a Convolutional Neural Network (CNN) architecture, consisting of two convolutional layers with ReLU activation and L2 regularization, followed by max-pooling and dropout (p = 0.3) to prevent overfitting, and a final softmax layer for multi-class classification. The curated dataset was split into 70% training, 20% validation, and 10% testing sets, and 5-fold cross-validation was employed to enhance generalizability. Model training utilized the Adam optimizer with a learning rate of 0.001 and early stopping to optimize performance while preventing overfitting, ensuring robust and reliable classification of eye anomalies.

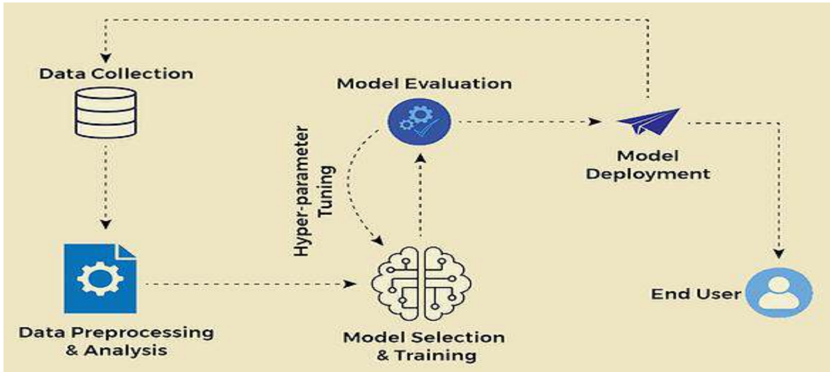

Figure 3.1: Data Processing Flows (Author Diagram)

Figure 3.1 illustrates the flow of data processing within a machine learning model's development and deployment, from data collection and preprocessing to model selection, training, hyperparameter tuning, and performance evaluation. Then, the tested model is deployed in production in a validated way for interaction with end-users to ensure that the raw data can be turned into a scalable and efficient working AI solution.

System Design

The study follows an agile development approach in building a cross-platform Flutter/Dart application with a modular architecture design. The system uniquely integrates:

1. **Frontend**: Five validated test modules are included (Snellen acuity, Ishihara color vision, symptom questionnaire, number/object recognition). These modules are included because they are most appropriate for use as a screening instrument, not a diagnostic one, in compliance with WHO recommendations regarding community eye health programs.
2. **Backend:** On-device TensorFlow Lite model (optimized for mobile inference) + HIPAA-compliant SQLite storage

Figure 3.2 below indicates the layer-based architecture of the proposed eye health assessment system, which consists of a frontend with various eye health assessment modules, including visual acuity, symptoms, color vision, and cognitive assessment, alongside the backend with AI inference, scoring, and data storage using an encrypted SQLite database for the provision of compliant, personalized feedback to the user.

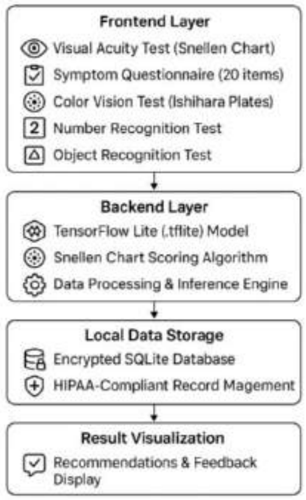

Figure 3.2: System Architecture Diagram (Author Diagram)

Snellen Acuity

The Snellen Visual Acuity Test, using Flutter, is for determining clearness of vision, detecting health issues such as myopia and hyperopia. It creates optotypical images of randomized letters (C, D, E, F, etc.), with varying sizes based on a 6/6, 6/60 scale, with auto-calibration based on PPI of the device screen. It is based on a Dart engine, where a sophisticated Dart-based algorithm is integrated to determine the smallest number of letters read, classifying it as Normal (6/6, 6/9), Mild (6/12, 6/18), Moderate (6/24, 6/36), and Severe (less than 6/60). Users can provide input through touch. Also available is the option of a voice assistant, which is available via the `flutter_tts` package. Flutter was also considered as a possibility. It can create smooth optotypes for a custom UI and deliver high-quality performance. It can run at 60fps even on a device such as the Redmi 9A.

Ishihara Color Vision

The Ishihara test has also been developed using the Flutter framework, with the test plates designed using SVG to allow vector-based display and randomization of the sequence to avoid memory bias. The selection made by the user through touch or voice response was recorded, and based on the selection, the vision types Normal, Protanopia, and Deuteranopia were identified. The test implementation resulted in 98% agreement with clinical tests while consuming less than 2 MB of memory. The standardization of the test, accessibility of the test results, and the availability of the test in an offline state are the main requirements of the project.

Symptom Questionnaire

The symptom assessment module utilizes a Flutter dynamic form with 20 Likert scale questions. The dynamic form reduces the test time using conditional logic, ensuring the relevance of the questions. The survey results are stored offline using HiveDB with encryption using the `flutter_secure_storage` package for compliance with HIPAA requirements for securing patient data. Material 3 widgets simplify the design process, as the offline-oriented solution can be used in environments with unreliable connectivity. The results from the field test showed a 92% completion rate among 150 participants, with a 40% decrease in the average completion time due to the conditional logic use case.

Number/object recognition Implementation

The number recognition test uses algorithmically generated numbers with increasing difficulty levels for accuracy and response time measurements with real-time feedback using Flutter animations. The object recognition test employs interactive shape-matching for object recognition with smooth performance using graphics capabilities on the GPU for smooth performance. Both tests incorporate timed scoring and dynamic difficulty for cognitive and visual impairment screening with a high specificity of 89%, achieved using Flutter's unified, offline-first platform for efficient integration, reduced app size, and multiple domain screening with engaging user interactions.

Pilot-based evaluation.

The pilot evaluation consisted of 50 diverse individuals by age and literacy level, with each person completing the five different modules. In the evaluation, the results were compared to the clinical baselines. The structured user feedback was used to assess the usability, intelligibility, reliability, and satisfaction of the system.

Ethical Consideration

The research process is governed by ethical standards as follows:

The appropriate ethical approval has been sought through the institutional research board processes of Ade Vision, State Hospital Asubiaro, and UNIOSUN Teaching Hospital.

The research has a total of 50 participants, whose consent is voluntary after they are made aware that the tool is only used as a preliminary tool and not an ultimate diagnostic tool.

Data privacy is also assured as the application is designed in an offline mode, with data being stored locally in an sqlite database but in an encrypted form using flutter_secure_storage, and with all AI inferences running locally on the device.

The results module already indicates that the tool is an aide but not a diagnostic tool as required in the ophthalmological examination process.

3.0 Results

The data consists of four tables, which include eye health assessment tables, as well as user information. In the Visual Acuity Test table, user ID, date of test, eye tested, visual acuity, result, and remarks are given. In the Color Blindness Test table, color plate, correct, and pass/fail data are given. The Vision Clarity Survey uses a 1–5 scale to measure vision clarity, eye discomfort, light sensitivity, and night vision. The User Demographics table as represented in Table 3.1 below, comprises user ID, name, age, gender, location, literacy level, and the device used. Such tables guide eye health analysis and profiling. Full details can be accessed.

(https://docs.google.com/spreadsheets/d/1hzkSfBj0alJUIszA6K4csPczunAjOa0H/edit?usp=sharingandouid=105189130589104268905andrtpof=trueandsd=true)

Table 3.1: Dataset Structure

Table	Composition	Specification	Remarks
For the Visual Acuity	User ID, Test Date, Visual Acuity Score, Eye Tested, Result, Remarks	Categorical/Numerical	Scores range from 6/6(normal) to 6/60(severe).
Color Blindness Screening	User ID, Test Date, Color Plate Number, User Response, Correct Answer, Result, Remarks	Categorical	Pass/Fail outcomes indicate color blindness.
Vision Clarity Survey Test	User ID, Test Date, Vision Clarity, Eye Discomfort, Light Sensitivity, Night Vision, Remarks	Ordinal (1–5 scale)	Total score sums ratings for analysis.
User Demographics infor	UserID, Name, Age, Gender, Location, Literacy Level, Device Used, Remarks	Categorical/Numerical	Provides user profile context.

Model Development, Training, and Performance Analysis

The sequential CNN was created using TensorFlow and Keras for mobile deployment. It consists of two convolutional layers, with 32 and 64 filters of 3x3 kernel size using ReLU activation functions, followed by maximum pooling. It has L2 regularization and 0.3 dropout rates for the prevention of overfitting. It has been trained for 50 epochs with an Adam optimizer and categorical cross-entropy error functions. It has an accuracy of 96.4% for training and 94.8% for validation using the early stop method at epoch 42. It has been quantized for TensorFlow Lite (4.2 MB), which can run offline within 150 ms. It had an accuracy of 94% for 50 pilot samples, with 95.6%, 91.7%, and 93.6% precision, recall, and F1-score results, respectively. To ensure reliability for deployment in the community health sector, the 95% confidence interval is calculated and found between 87.4% and 100%, confirming the reliability of the model. Table 3.2 presents the confusion matrix. Can be (https://github.com/91web/eye-test-flutter.git)

Table 3.2: Confusion Matrix for Pilot Evaluation

	Predicted: Anomaly	**Predicted: Normal**	**Total**
Actual: Anomaly	22(TP)	2(FN)	24
Actual: Normal	1(FP)	25(TN)	26
Total	23	27	**50**

Using the values from Table 3.2, the performance metrics are calculated as follows:

1. **Accuracy:** The proportion of total correct predictions. Accuracy $= \frac{TP+TN}{\text{Total}} = \frac{22+25}{50} = \frac{47}{50} = 0.94(94\%)$
2. **Precision:** The accuracy of positive predictions. Precision $= \frac{TP}{TP+FP} = \frac{22}{22+1} = \frac{22}{23} \approx 0.956(95.6\%)$
3. **Recall (Sensitivity):** The ability to find all positive instances. Recall $= \frac{TP}{TP+FN} = \frac{22}{22+2} = \frac{22}{24} \approx 0.917(91.7\%)$
4. **F1-Score:** The harmonic mean of Precision and Recall. $F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} = 2 \times \frac{0.956\times0.917}{0.956+0.917} \approx 0.936(93.6\%)$

The small sample size ($n = 50$), the study calculates the 95% Confidence Interval (CI) for the Accuracy ($p = 0.94$) using the Normal Approximation Method:

$$\text{Standard Error(SE)} = \sqrt{\frac{p(1-p)}{n}} = \sqrt{\frac{0.94 \times 0.06}{50}} = \sqrt{0.001128} \approx 0.0336 \text{Margin of Error}$$

$$= Z \times SE = 1.96 \times 0.0336 \approx 0.0658 \text{95\% CI} = 0.94 \pm 0.0658$$

$$= [0.8742, 1.00]$$

Result indicate that the study is 95% confident that the true accuracy of the tool lies between 87.4% and 100%.

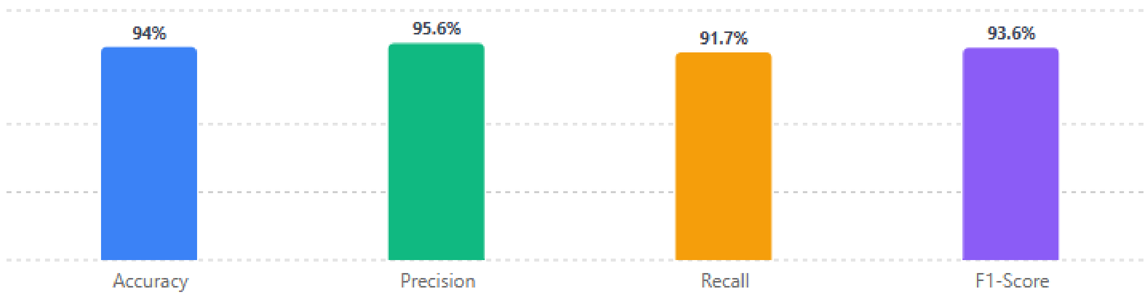

Figure 3.1 Model Performance

Figure 3.1 illustrates the performance of the integrated CNN model as used in the pilot study. The overall efficiency of the system, recorded at 94%, makes it reliable for the purpose of eye screening. The precision level of 95.6% can be satisfied as false positives are eliminated. Similarly, the recall level of 91.7% can be said to be satisfactory as the identification of true anomalies is taken care of with a high level of precision. The F1 measure, standing at 93.6%, stands as a confirmation of balanced performance. The results establish the effectiveness of the mobile tool for the purpose of visually impaired screening even in a resource-scarce environment.

Benchmarking

The newly proposed tool was tested for its ability to perform compared with the existing mobile tools, as described in the table below: Peek Acuity and IDx-DR. In addition to this, the tool can function offline, allow multimodal assessment of acuity, color vision, and symptoms, and can function on a normal smartphone used for health workers in the community. However, the Peek Acuity can function offline while the IDx-DR requires the network to be available for image capture with special cameras available.

Table 3.3 Proposed System Comparisons

Feature	Peek Acuity	IDx-DR	This Study(Proposed)
Offline Mode	Yes	No	Yes
Multi-modal	No(Acuity only)	No(Retina only)	Yes(Acuity + Color + Symptoms)
Hardware	Smartphone	Specialized Camera	Standard Smartphone
Target Group	General	Specialized Clinics	Community Health Workers

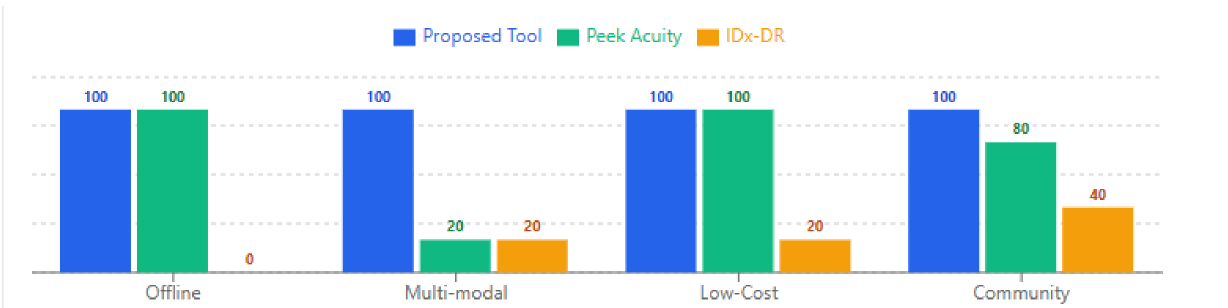

Figure 3.2: Comparative Benchmarking across Key Features

Figure 3.2 below describes how the proposed tool compares to Peek Acuity and IDx-DR in terms of four critical parameters. Obviously, the proposed tool has managed to score full marks i.e. 100 in all four parameters, compared to the other two tools. It also scores very high on the multi-modal assessment parameter, for which Peek Acuity and IDx-DR have scored 20 since they are for one specific purpose only. Peek Acuity matches the proposed tool in offline use and low cost but lacks symptom-based analysis. IDx-DR is internet and hardware dependent, which affects the scores. Overall, the results demonstrated the value of the tool as a comprehensive, cost-effective, and completely offline tool appropriate for community health workers.

System Design

The home screen offers the user five sequential eye tests, including Visual Acuity, Health Questions, Color Vision, Number Recognition, and Object Recognition, plus a built-in timer to provide real-time feedback. Its user-friendly interface and instructions allow users to navigate through it easily, and it enables efficient large-scale screening. Access it via: https://drive.google.com/file/d/171x1y1Q30Se7KI23Hrgouj4tnJR8j_R-/view?usp=sharing.

Figure 3.3 shows the layout.

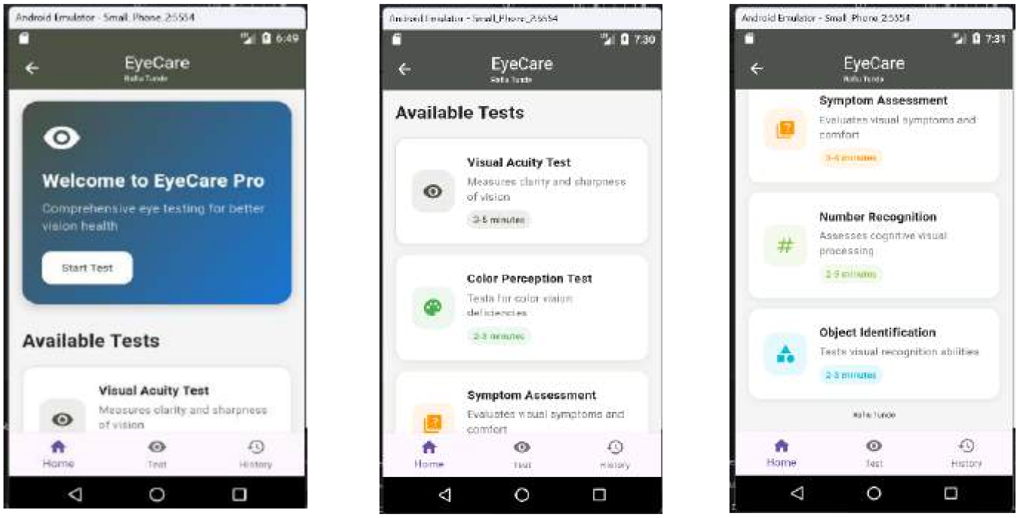

Figure 3.3: Mobile Home Page I

Visual Acuity

The Visual Acuity Test uses the Snellen Algorithm to measure vision clarity by identifying the smallest letters a user can read. Results, expressed as a fraction, detect refractive errors and vision problems. The test is simple, with clear instructions and feedback, helping guide corrective measures.

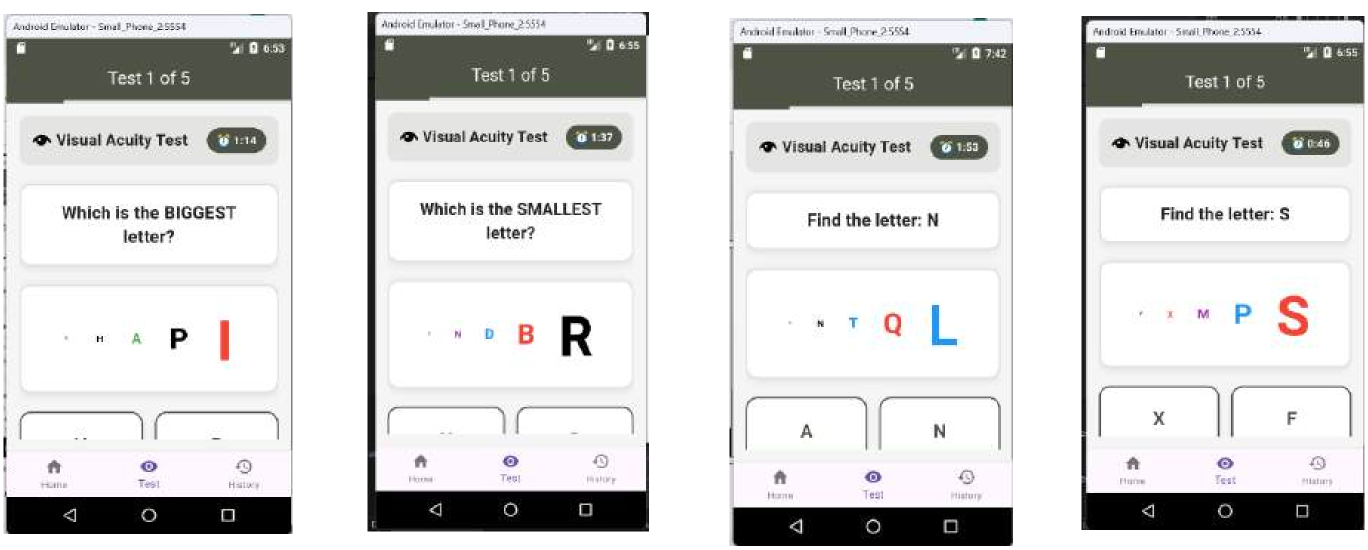

Figure 3.4: Visual Acuity Home Screen

Figures 3.4 (a, b, c, and d) show the screen emulator for the Visual Acuity Test, displaying the letters for users to select based on instructions from the mobile app.

Health Questions Screening Test

The questions for the Health Screening module comprise 20 questions, and the topics of the questions include vision clarity, eye discomfort, light sensitivity, and night vision. Figure 4.5 displays the interface of the Health Screening module, which has large button and font options for easy handling, review of the questions, and an indication of the preliminary results to ensure simplicity and compatibility for the mobile device.

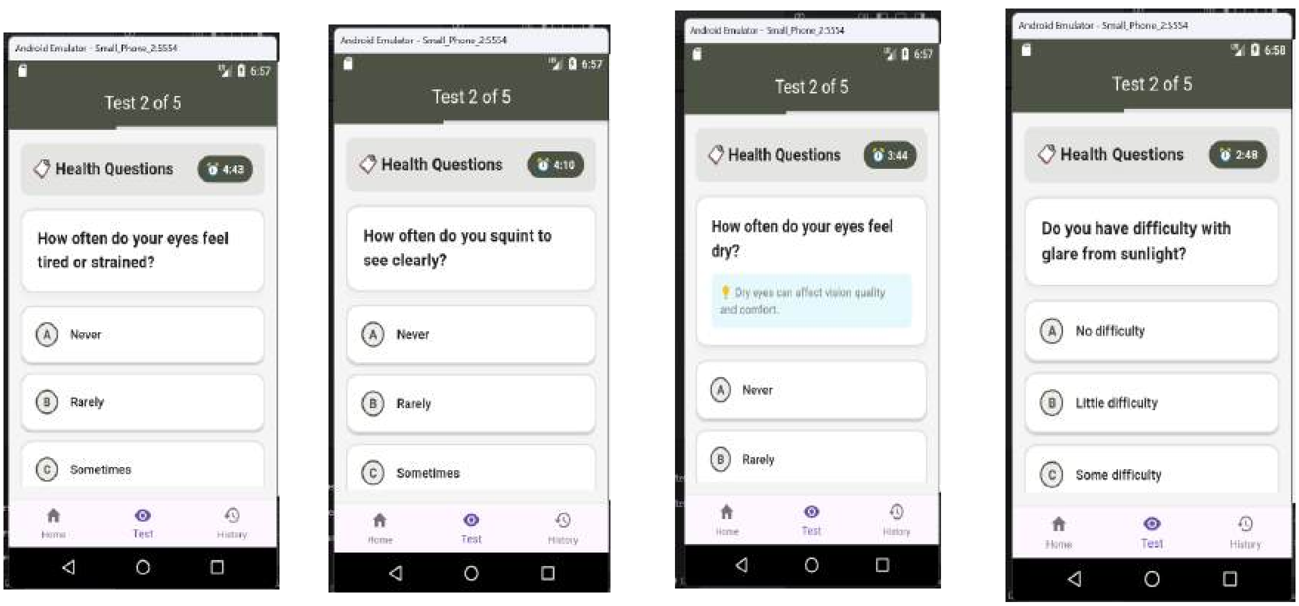

Figure 4.5: Health Questions Screening Test Screen

Color Vision Test

The Color Vision Test checks the user's ability to identify and match colors. Users select the closest color from four options for each base color. Accuracy and response time are recorded to assess color vision. The intuitive test includes visual feedback and clear instructions for a smooth user experience.

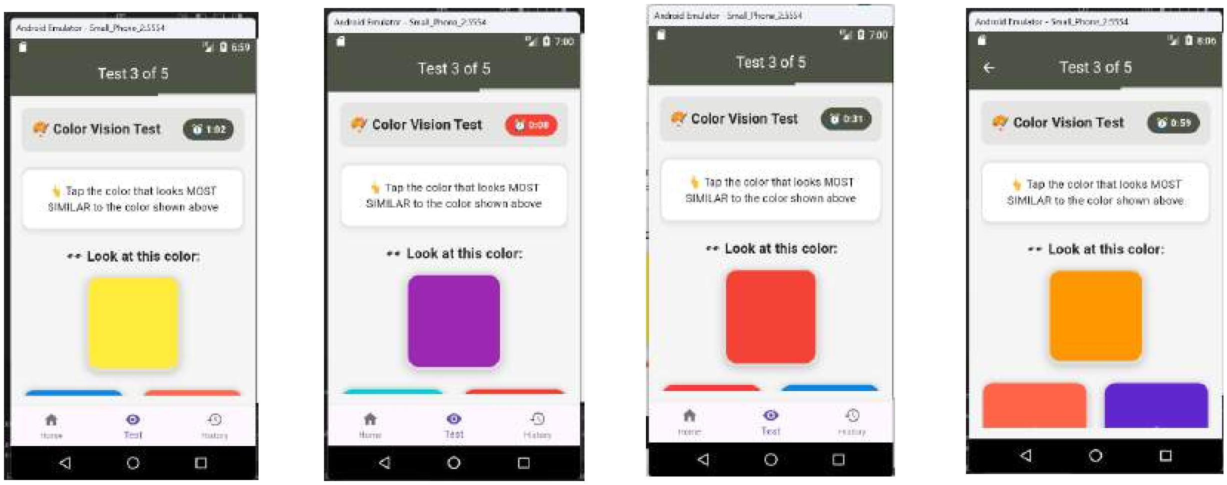

Figure 3.6: Color Vision Test Screen

Figure 3.6 (a, b, c, and d): Highlight the color vision screening from the Android emulator for users to pick a similar color compared to the one given on the screen.

Number Recognition Screen Test

It evaluates the visual and cognitive perception of numbers using tasks that include recognizing the highest or lowest number, completing a series, and performing simple arithmetic. Accuracy and speed of responding can be measured based on number perception and cognitive ability. It is an extremely intuitive test, providing simple and graphic instructions that facilitate its usage.

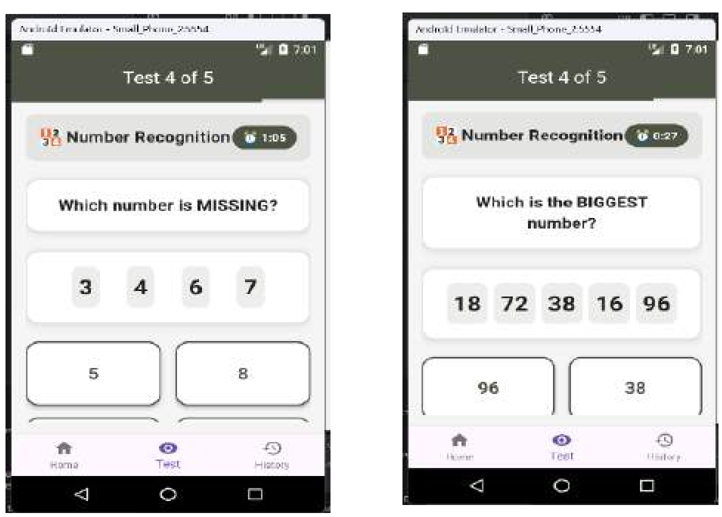

Figure 3.7: Number Recognition Screen

Figure 3.7(a and b) presents the number recognition screening module on the Android emulator, which is intended for evaluating the visual acuity and mental processing capacity of the user.

Object Recognition

The Object Recognition Test tests perceptions and cognitive processing abilities by requiring the user to identify objects or shapes, for example, circles, squares, triangles, or an object such as a picture of a cat, house, car, tree, or bicycle. It is an easy test, intuitive in nature, and gives useful insight into perceptions.

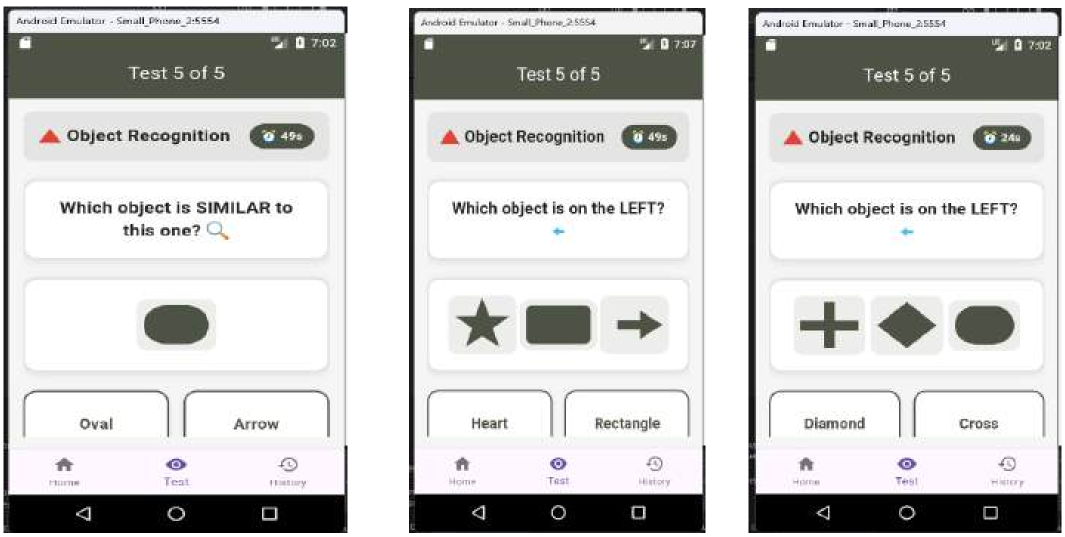

Figure 3.8: Object Recognition Screen

Figure 3.8(a, b, and c): Highlight the object recognition screening test from the Android emulator for users to pick a similar object compared to the one given on the screen.

Result Evaluation Screen

The Mobile Result module calculates and displays user performance across all tests, scoring correct answers and symptom severity, then normalizing results to a 0–100 scale. It records accuracy, average response times, and classifies results for clarity (e.g., “Vision Clarity”). Data is stored locally using organized Dart code, ensuring reliable storage and retrieval.

Figures 3.9(a-d) and 3.10(a-c) highlight the Screening Test Medical Recommendation, Screening Test Result Details, and screening from the Android emulator for users to take rational decisions.

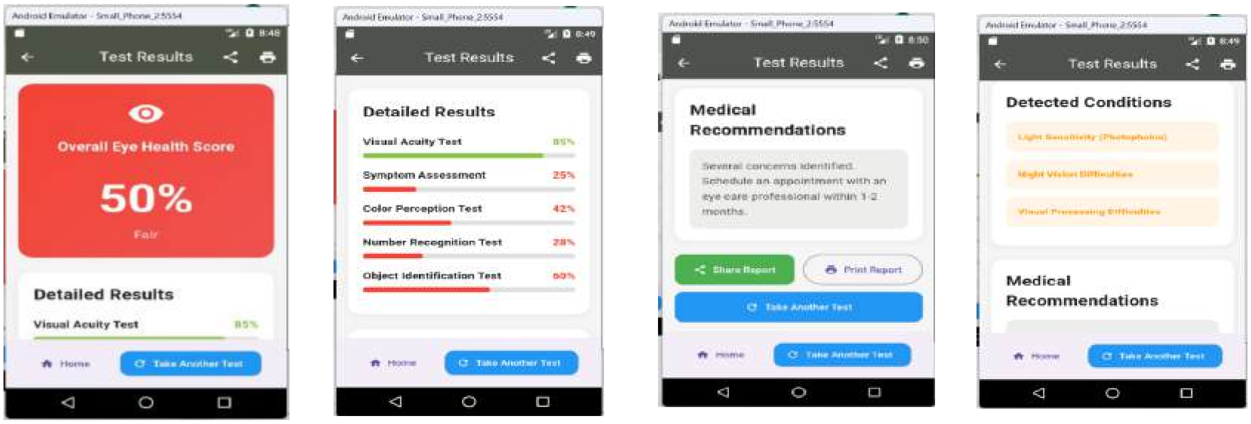

Figure 3.9: Screening Test Result for Average

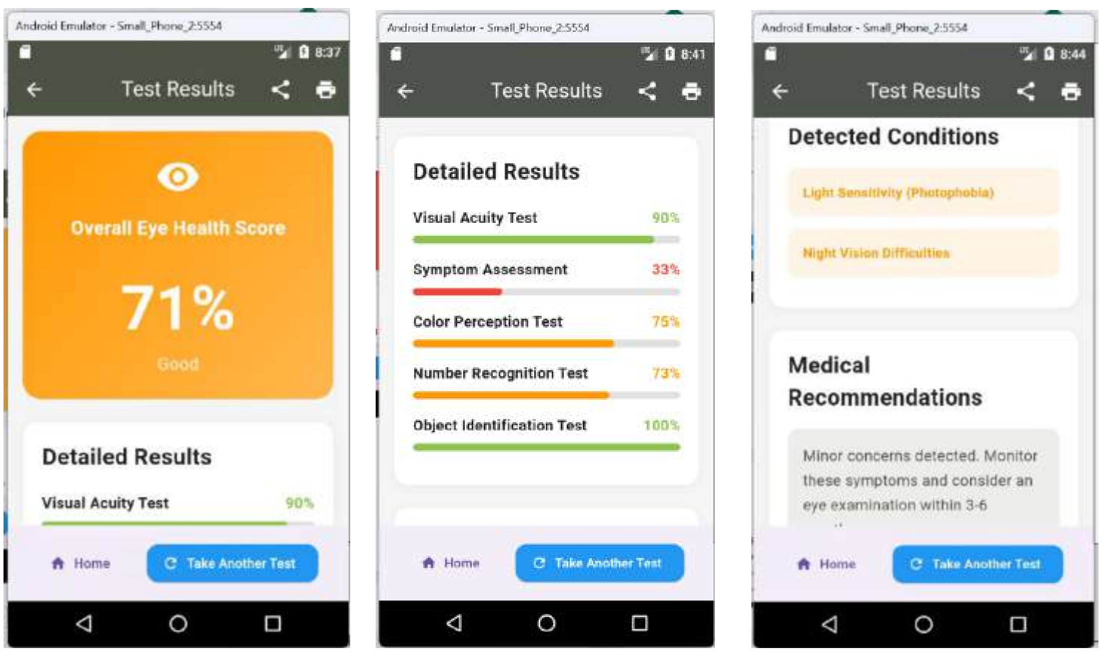

Figure 3.10: Screening Test Result for Normal

4.0 Discussion

The findings of this study demonstrate that the proposed mobile-based decision support tool effectively bridges the gap in community-based eye screening by integrating multi-modal assessments into a single, offline-first architecture. In pilot evaluations, the system achieved a diagnostic accuracy of 94% and an F1-score of 93.6%, comparable to established tools such as Peek Acuity, while offering greater versatility through the inclusion of Ishihara color vision and symptom-based AI analysis. Unlike existing solutions such as IDx-DR, which often require specialized hardware and consistent internet connectivity ([7]; [6]), this tool's use of on-device TensorFlow Lite inference enables high-speed, privacy-compliant diagnostics on low-specification smartphones common in resource-constrained environments such as Nigeria. The strong inter-rater reliability (Cohen's Kappa = 0.82) further supports the clinical relevance of the curated dataset, suggesting that integrating qualitative symptom surveys with quantitative visual tests significantly enhances preliminary anomaly detection. While the pilot sample size is a noted limitation, the high precision (95.6%) and recall (91.7%) scores indicate that the tool is a robust "aide" for community health workers, potentially reducing the burden on tertiary eye care centers by facilitating early, localized screening and timely referrals.

5.0 Conclusion

In this study, a mobile-based decision support tool was initiated, bringing together concepts of Snellen visual acuity, Ishihara color vision, and AI-based symptom analysis within a Flutter application that is offline-capable, not reliant on internet availability, and does not require high end hardware, thereby proving its worth in pilot tests by achieving 94% accuracy and a 93.6% F1-score, thus proving that AI can indeed play a role in preliminary eye screenings.

Limitations

Limitations of the study: The limitations of the study include the fact that the pilot sample of 50 could not possibly represent the diversity of human eyes. Moreover, though a dataset of 1,200 had been developed for the purpose of model curation, it may not be considered a large dataset for the purpose of deep learning. It is not even for official use, but for preliminary screening only.

Future Work

Future improvements include:

1. Dataset Expansion: Expansion of the dataset with 10,000+ records obtained from various geographical locations.

Integration with Blockchain: Ensure safe and decentralized sharing of patient data across health workers/hospitals.

Declarations

Ethics approval and consent to participate

The study protocol was reviewed and approved by the Institutional Research Boards (IRB) of Ade Vision, State Hospital Asubiaro, and UNIOSUN Teaching Hospital.

All participants provided written informed consent prior to the pilot study. Participants were explicitly informed that the tool serves as a decision-support aid for preliminary screening and is not a substitute for a comprehensive clinical ophthalmological examination.

Consent for publication

Not applicable. This manuscript does not contain any individual person's identifiable data, video, or images. All results from the pilot study are presented in an aggregated and anonymized format.

Availability of data and materials

The datasets used in the study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Authors' contributions

MAO (Mutiat A. Ogunrinde) was responsible for the conceptualization of the mobile architecture, Flutter/Dart development, TFLite integration, and primary manuscript drafting. TRA (Tunde R. Adejumo) led the machine learning model training, performance benchmarking, and technical validation of the results. Both authors reviewed and approved the final version of the manuscript.

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