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Smart System to Enhance Medical Examinations Data Analysis for University Students

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Abstract

Mobile health (mHealth) applications have revolutionized the healthcare sector by providing innovative solutions for patient monitoring, health tracking, and medical consultation. These applications leverage the widespread use of smartphones to deliver health services that are accessible, affordable, and efficient. Research indicates that mHealth technologies significantly improve healthcare service delivery processes, enhancing patient outcomes and healthcare management. Furthermore, the functionality of mobile apps in health interventions has been systematically reviewed, showing positive impacts on user engagement and behavior change. This study explores the development and implementation of a medical screening application for incoming university students using an Android platform. The application is designed to perform basic health check-ups, including monitoring and assessing general health status, and providing recommendations for further medical consultation if necessary. The application includes several modules: blood test analysis, vision test, hearing test, and speech test. By leveraging advancements in mobile health (mHealth) technologies and artificial intelligence, the application offers a cost-effective and scalable solution for university health services. This paper highlights the potential benefits, challenges, and future implications of deploying mobile health screening applications in educational institutions.

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1. Introduction

The implementation of medical screening application for incoming university students plays a crucial role in safeguarding their health and ensuring a safe educational environment [1]. These screenings often encompass vision tests, hearing tests, speech evaluations, and blood tests, which help in identifying any underlying health issues that might affect the students' well-being and academic performance. The integration of Android applications in this process offers a convenient and efficient solution, enabling universities to conduct comprehensive medical screenings swiftly and accurately. This technological advancement can significantly reduce the workload on medical staff and provide timely health assessments for students [2].

Medical screening has been recognized as a pivotal component in the early detection and prevention of health issues among students. Studies have shown that early diagnosis and intervention can lead to better health outcomes and improve the overall quality of life for students. Furthermore, the use of mobile health applications has been associated with increased accessibility and adherence to health protocols [3][4].

The primary objective of this research is designing and implementing an Android application for pre-college student health screening, evaluating the effectiveness of the application in detecting health issues, and providing a user-friendly platform for universities to assess student health and their fitness to enter university.

2. Related Work

Morawski et al. studied the effectiveness of a smartphone app for self-management of hypertension App. MedISAFE-BP combines medication reminders with blood pressure tracking. Patients receive medication reminders and can log their blood pressure readings. The app provides visualizations of blood pressure trends over time. This study found a small but statistically significant improvement in systolic blood pressure among app users [5]. Armstrong et al. evaluated a mobile app for monitoring recovery after colorectal surgery. SeamlessMD application guides patients through recovery, allowing them to track symptoms and receive educational content. Patients input data on pain levels, wound healing, and other recovery milestones. The app provides tailored educational content and alerts healthcare providers to potential complications.

The study found high patient engagement and satisfaction, with potential for reducing hospital readmissions [6]. Swanepoel, D introduced hearScreen App,which transforms smartphones into calibrated hearing screening devices. It uses pure tone audiometry to test hearing at different frequencies. The app includes ambient noise monitoring to ensure accurate results in various environments and is designed for use in both clinical and community settings [7]. Ali, Amonah & Fallatah, Maryam developed an android application that can translate incomprehensible speech into understandable speech and may improve the pronunciation of words to help those people in communicating and their speech would be clear. Be my voice application will support android operating system and Arabic and English interfaces. It can help people with speech difficulties in communicating and to feel much better because it will allow people to understand them and all those people want is to be understood [8].

3. Background

As smartphone technology continues to advance, amazing concepts have been created to make use of all the resources and capabilities built into smartphones. To maximize the effectiveness of the suggested system in medical screening for precollege students, we employed a number of tools and integrated technologies in our application. These technologies and tools are described in the next section.

A. Android Platform

The Android operating system, launched by Google in 2008, has grown to become the most widely used mobile platform in the world. Powering billions of devices ranging from smartphones and tablets to wearable technology and smart home devices, Android dominates the global market with over 70\% market share in mobile operating systems. Its open-source nature, extensive developer community, and robust ecosystem have made Android software development an essential skill for modern technologists [9].

B. Java Programming language

With Android application development, Java is one of the most often employed programming languages; it is still habitually used today and has been the main language for Android development since the platform's float. Programming apps is made much elementary by the cluster of libraries and frameworks accessible in Java. Java operates in virtual machines; consequently, code does not need to be recompiled for each gadget. Java provides an immense array of libraries and frameworks that substantially streamline the process of developing apps. It comprises numerous admired development tools, inclusive of Eclipse, NetBeans, and much more. Java is the programming language of option for app developers who issue Java development services because of its powerful toolkit [10].

C. Firebase

Firebase is considered as web application platform. It helps developers‟ builds high-quality apps. It stores the data in JavaScript Object Notation (JSON) format, which does not use query for inserting, updating, deleting or adding data to it. It is the backend of a system that is used as a database for storing data. Firebase provides services like a real-time database and backend [11].An API is provided to the application developer that allows application data to be synchronized across clients and stored on Firebase's cloud. The company that enables integration with Android, IOS, and JavaScript applications provides the client libraries. It facilitates easy and secure file transfer regardless of network quality for the Firebase apps. Google Cloud Storage backs it, which is cost-effective object storage service. The developer can use it to store images, audio, video, or other user-generated content [12].

D. Google's ML Kit Text Recognition

Text recognition, commonly known as Optical Character Recognition (OCR), is a technology that recognizes text from images and converts the recognized text into a machine readable text . This technology has been widely adopted in various applications such as document scanning, data entry, and information retrieval. OCR technology works by analyzing the image and identifying patterns and features that correspond to characters, numbers, and symbols. These patterns are then compared against a predefined set of templates, which are used to determine the character or symbol represented by each pattern [13].

E. Google's Speech Recognition

Speech recognition for application is done on Google server or on the same device based on the Android version and user choice. Process involves the conversion of speech into a set of words and is performed by software component. [14]

4. Proposed System Proposed System Architecture and Module Descriptions

The proposed Android application is engineered as a comprehensive health-screening tool, structured around four pivotal modules designed to assess distinct aspects of a student's physiological well-being. These modules are: (i) Blood Test Analysis, (ii) Vision Acuity Assessment, (iii) Auditory Function Evaluation, and (iv) Speech Clarity Analysis fig (1). The system's architecture promotes a modular and scalable design, allowing each component to function independently while contributing to an integrated health profile. The overall conceptual framework emphasizes a user-centric interface that guides students through each screening procedure, facilitates secure data input, and employs robust analytical techniques to derive meaningful health insights.

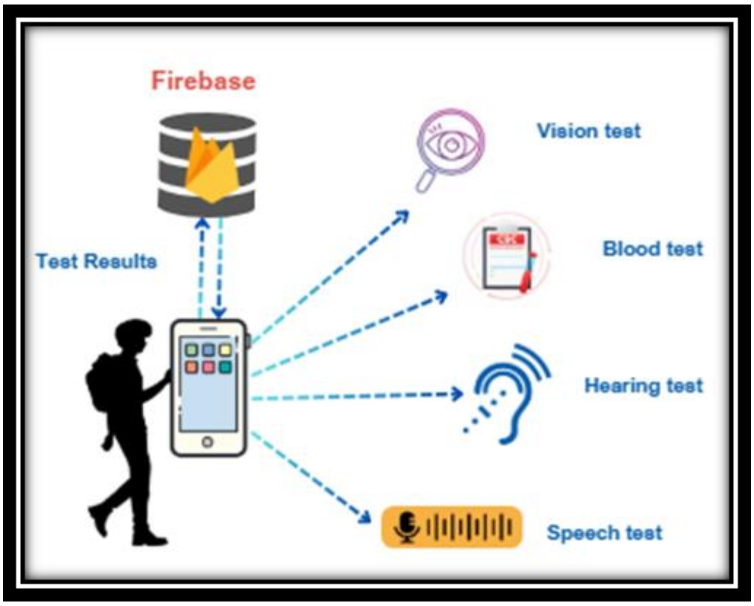

Figure 1. System conceptual diagram

a. Blood Test Analysis Module

The Blood Test Analysis module is designed to automate the interpretation of standard blood test reports. Users upload an image of their blood test results, which the system processes using Google's ML Kit Text Recognition technology fig (2). This technology performs Optical Character Recognition (OCR) to extract textual data, such as specific analytic values (e. g., hemoglobin levels, glucose concentrations, white blood cell counts) and their corresponding units [15]. The core of the analytical process involves a rule-based engine where extracted numerical values are systematically compared against predefined, medically accepted reference ranges. These thresholds are categorized by age and gender where applicable, to ensure contextual accuracy. Mathematically, if an extracted value V_e for a parameter P falls outside its normal range $[L_P, U_P]$, where L_P is the lower limit and U_P is the upper limit, it is flagged as an abnormality. For instance, if $V_e < L_P$ or $V_e > U_P$, the system registers a potential issue. The module is engineered to handle variations in report formats and to provide a preliminary assessment, highlighting any values that deviate from the norm and warrant further medical attention. This automated approach aims to provide rapid, initial screening, enhancing the efficiency of health assessment processes.

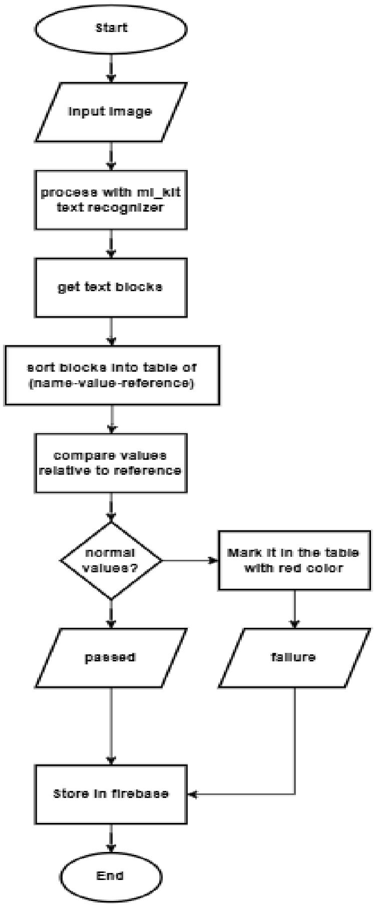

Figure 2. Blood Test analysis

b. Vision Acuity Assessment Module

The Vision Acuity Assessment module employs principles derived from standardized ophthalmological tests, specifically adapting the Landolt C chart methodology [16]. The Landolt C is an optotype consisting of a ring with a gap, resembling the letter 'C'. The orientation of this gap (e. g., top, bottom, left, right, or intermediate diagonal positions) is varied systematically. The test presents a sequence of these optotypes to the student, typically at a standardized viewing distance simulated on the mobile device's screen, or with instructions for maintaining, a correct physical distance the student's task is to identify the orientation of the gap for each presented Landolt C. The size of the optotype is progressively reduced, or the viewing distance effectively increased, to determine the visual acuity threshold.

c. Auditory Function Evaluation Module

The Auditory Function Evaluation module is designed to perform a basic hearing screening using pure-tone audiometry principles [17]. The application generates and delivers pure tones at various standard frequencies, typically spanning the critical range for speech comprehension, such as 100 Hz, 250 Hz, 500 Hz, 1000 Hz, 2000 Hz, 4000 Hz, and 8000 Hz fig (3). These tones are presented to the student, usually through headphones connected to the mobile device to ensure controlled sound delivery and minimize ambient noise interference for each frequency, the intensity (loudness, measured in decibels Hearing Level, dB HL) of the presented tone is varied, often using an adaptive procedure like the Hughson-Westlake method. The student is instructed to indicate whether they can hear the tone, typically by pressing a button on the screen. The system records the lowest intensity level at which the student consistently responds for each frequency, known as the hearing threshold. Mathematically, the hearing threshold \(T_f\) at frequency \(f\) is the minimum sound pressure level \(SPL_f\) that elicits a response. A plot of these thresholds across frequencies forms a basic audiogram. Deviations from established normal hearing thresholds (e. g., thresholds consistently above 20-25 dB HL) may indicate potential hearing loss, prompting a recommendation for a comprehensive audiological examination. The module aims to identify individuals who may require further testing for hearing impairments.

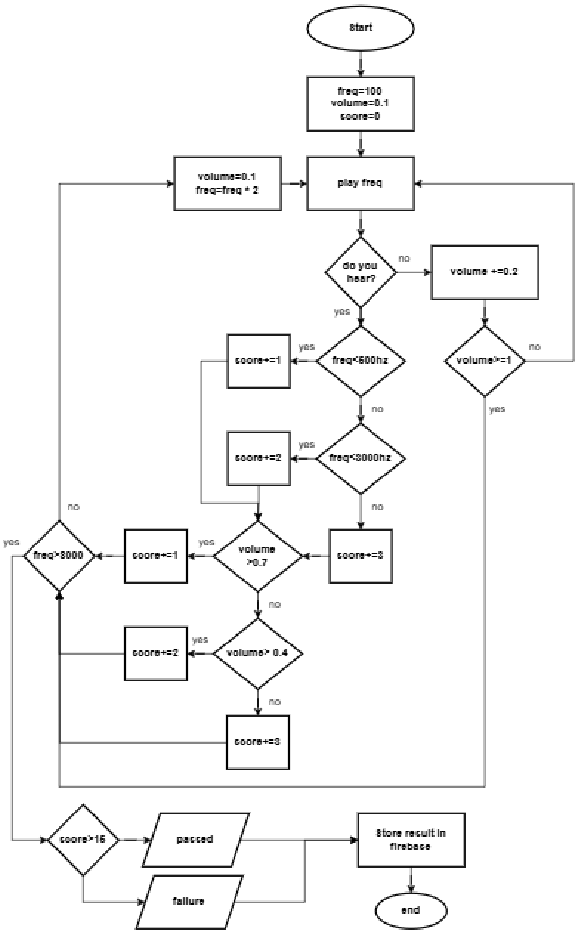

Figure 3. Auditory Function Evaluation Flowchart

d. Speech Clarity Analysis Module

The Speech Clarity Analysis module assesses the student's ability to produce clear and intelligible speech. This is achieved by prompting the student to articulate a predefined set of phonetically balanced words or sentences. The application utilizes the device's microphone to capture the student's speech. The recorded audio is then processed using Google's Speech Recognition API or an equivalent embedded speech-processing engine [18] the analysis focuses on several acoustic and phonetic features. The speech recognition engine attempts to transcribe the spoken utterances. The accuracy of this transcription, when compared to the target sentences, provides a primary measure of intelligibility. Further analysis may involve extracting prosodic features (e. g., pitch contours, speech rate, rhythm) and spectral characteristics (e. g., formant frequencies) to identify potential deviations indicative of speech disorders. For instance, a mathematical model might compare the recognized phonemes against expected phonemic targets, calculating a similarity score or error rate. Parameters such as articulation rate (syllables per second) or the presence of dysfluencies (e. g., stuttering) can also be algorithmically estimated. The module aims to screen for common speech impediments or articulation difficulties, suggesting further specialist assessment if significant deviations are detected.

5. Methodology

The application was developed utilizing Android Studio, with Java serving as the primary programming language. The development journey commenced with a thorough requirement analysis phase, where both functional and non-functional needs of the application were identified. This included defining requirements for user authentication, data storage, and various health screening modules. Figure (4) illustrates the main system flow chart. Following the analysis, the design phase focused on creating the application's user interface using XML on Android SDK-27. A modular architecture was also designed to distinctly separate modules for blood tests, vision tests, hearing tests, and speech tests (details for its figure reference were not provided in the original text). Furthermore, Firebase Database was integrated to ensure secure storage of student data and their test results.

From a user's perspective, the program initiates with a login screen. Existing registered users can log in with their username and password, while new users have the option to register by clicking the "Sign Up" button. The registration process involves new users completing a form with their details, such as name, phone number, and college affiliation. After successfully filling out the form, they create a username and password for subsequent logins. All this information is securely stored in the Firebase Database, allowing for easy retrieval.

Once logged in, the user starts with a preliminary test. This involves uploading an image of their blood test report. The application then employs Google's ML Kit Text Recognition to extract textual information from the uploaded image. These extracted values, for instance, haemoglobin and glucose levels, are subsequently compared against predefined thresholds to identify any potential abnormalities. Should any abnormalities be detected, the program flags the user for further evaluation. After completing the blood test, the user can then proceed to more advanced tests.

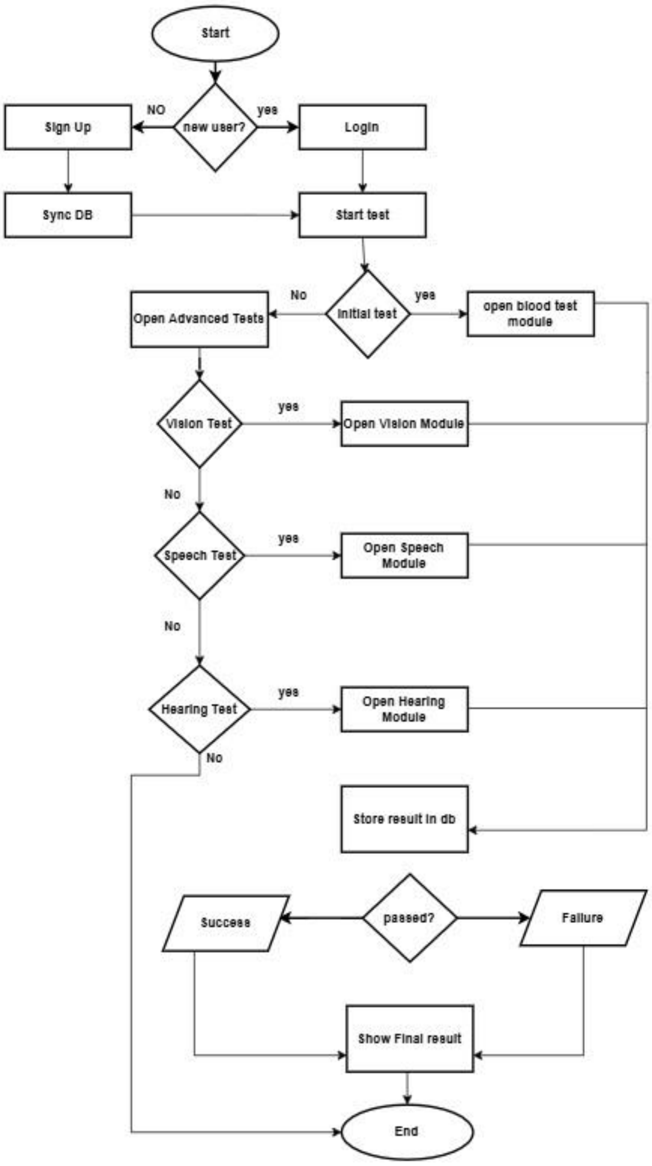

Figure 4. System Flow Chart

a. Vision Test

The program displays a series of images with circle openings in random positions. The user identifies the position of the circle opening (e. g., top, bottom, left, right).

b. Hearing Test

The program plays sound frequencies ranging from 100 Hz to 8000 Hz. The user indicates whether they hear the sound by clicking a button. The program evaluates the responses to detect hearing impairments.

c. Speech Test

The program prompts the user to pronounce specific sentences • The user's speech is recorded and analyzed using Google speech recognition algorithms • The program evaluates the clarity and accuracy of the pronunciation to detect speech disorders. d. Final Report Page • After completing all tests, the program displays the results page • The results determine whether the user is fit or unfit to join the university If the user has a health issue, the program: o Identifies the specific problem (e. g., blood abnormality, vision problem) o Recommends whether the user needs medical consultation • The results are stored in the Firebase Database for future reference.

d. Final Report Page

After completing all tests, the program displays the results page. The results determine whether the user is fit or unfit to join the university, If the user has a health issue, the program identifies the specific problem (e.g., blood abnormality, vision problem).Recommends whether the user needs medical consultation. The results are stored in the Firebase Database for future reference.

6. Testing and Experimental Results

In this study, our medical screening application was tested on 100 pre-college students under various controlled and real-world conditions. These metrics evaluate not only the clinical performance of each screening module (vision, hearing, speech, and blood analysis) but also the impact of environmental and system factors on the app's overall reliability and usability. The performance of each screening module was evaluated based on its accuracy, false positive rate, and false negative rate. Figure (5) illustrates the accuracy metrics for the blood test, vision test, hearing test, and speech test modules. The vision test module demonstrated the highest accuracy at 94%, while the speech test module had an accuracy of 89%, primarily attributed to variations in pronunciation and ambient noise during testing.

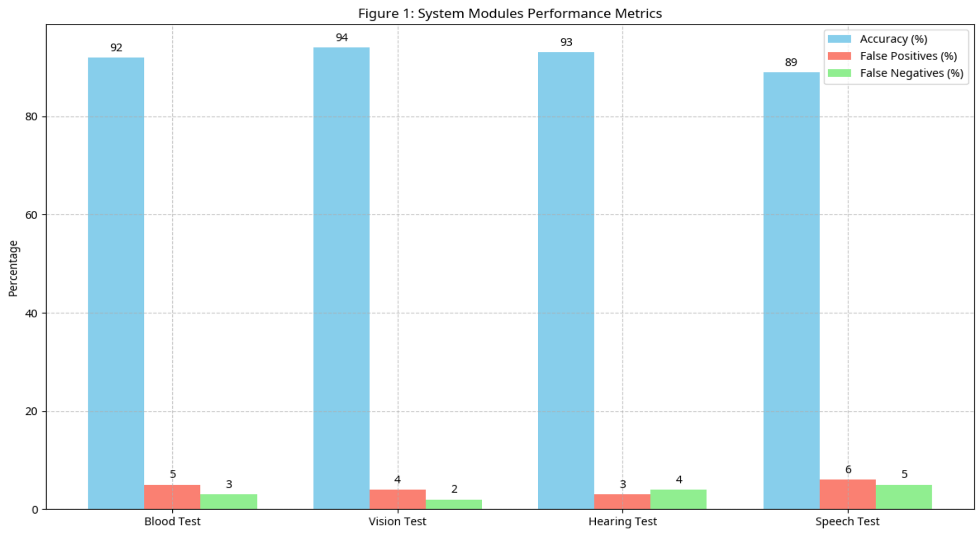

Figure 5. Module Accuracy

Out of the 100 pre-college students screened, various health issues were identified. Figure (6) presents the distribution of these detected health issues, including blood abnormalities, vision problems, hearing impairments, and speech disorders. Significant portions of students, 55%, were found to have no detectable issues through this screening process.

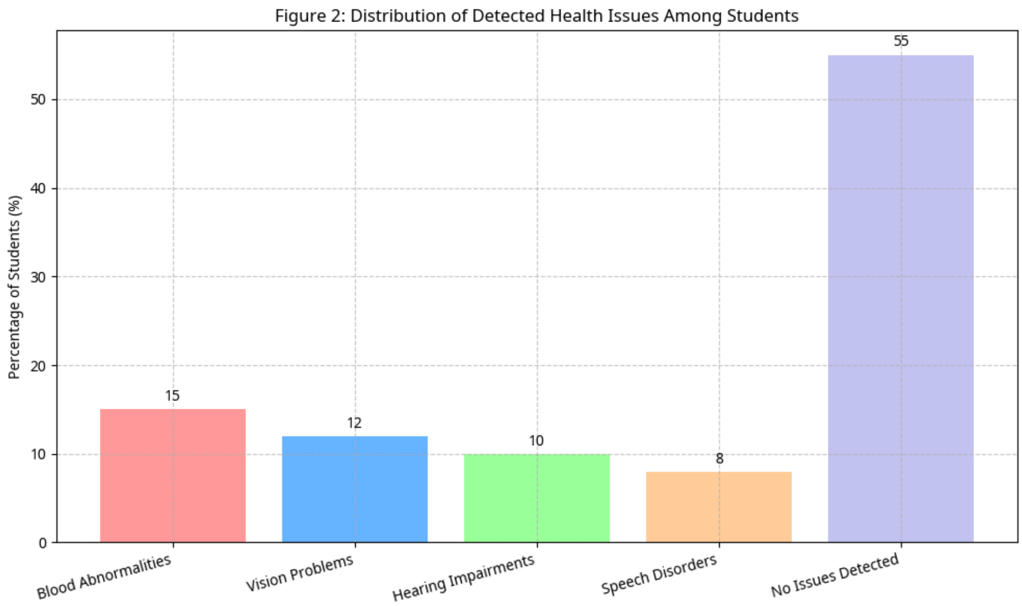

Figure 6. Health Issues Detected

The application's user interface received Positive feedback from students, with 90% of participants finding it easy to use. The integration of multiple health screening modules into a single platform was also praised for its convenience and efficiency

a. Environmental Metrics

For Vision Module, the ambient light level is a key metric, measured in lux (lx) using the device's built-in light sensor. The target or expected range for this measurement is between 300 and 800 lux, which corresponds to standard indoor lighting conditions. The rationale behind monitoring this metric is that changes in lighting conditions can significantly affect the clarity and accuracy of the captured vision test images. Subsequently, image quality is assessed based on several metrics. Resolution, measured in pixels, ensures that the captured image meets a minimum clarity standard. Additionally, the contrast ratio and sharpness are evaluated using in-app image processing algorithms. Maintaining high image quality is crucial for accurately extracting data from the vision charts.

For the hearing and speech modules, the ambient noise level is an important factor. This level is measured in decibels (dB) using the device's microphone or an external sound meter, with a target or expected range of ≤50 dB to ensure a quiet environment. The reason for this is that high noise levels can negatively affect the quality of audio recordings, thereby affecting test accuracy. Another critical metric is the Signal-to-Noise Ratio (SNR), which is calculated during audio capture for both hearing and speech tests. An SNR of ≥20 dB is targeted, as a higher SNR indicates that the audio signal is clear relative to background noise, leading to improved test evaluation accuracy.

Finally, in the blood analysis module, the clarity of lab report images is paramount. This is evaluated based on metrics such as resolution, requiring the image to have a resolution of at least 300 dots per inch (dpi), and the focus/blur level, which is quantified using algorithms that assess image sharpness. The importance of high-quality images in this context lies in their necessity for accurate Optical Character Recognition (OCR) performance when extracting clinical data from the reports.

b. System Performance Metrics

Performance metrics are crucial for evaluating the application's efficiency and reliability. The processing time per module, measured in seconds from data capture to result generation, is targeted to be less than 5 seconds per module. This swift processing is important as short processing times reduce user wait periods and enhance the overall efficiency of the application. Another key performance indicator is the OCR accuracy rate, which is the percentage of correctly recognized text when compared to manually reviewed data. The target for this metric is an accuracy of 95% or higher, a critical standard for both the vision and blood analysis modules to ensure data integrity.

In terms of audio processing, accuracy is measured by the transcription error rate when converting speech to text, benchmarked against a standardized transcript. An error rate of less than 10% is the expected outcome, ensuring that the speech recognition feature accurately transcribes spoken language. Furthermore, the stability of the application is monitored through error and crash rates, which record the number of errors or application crashes during testing sessions. The desired outcome here is minimal or zero crashes, as a stable, crash-free application is essential for building user trust and ensuring reliability.

Finally, resource management is assessed through battery consumption and memory usage. Battery consumption is tracked as the percentage of battery used during a testing session, while memory usage statistics are recorded by the app during its processing tasks. Efficient resource usage is vital to ensure the app performs well across various devices without causing excessive battery to drain or memory overload.

To further evaluate the system's efficacy, several standard performance metrics were calculated for each module based on the 100 student tests. These include accuracy, precision, recall (sensitivity), and the construction of confusion matrices to visualize the classification performance.

- **Blood Test Analysis Performance:**

With an accuracy of 92.00%, it successfully classified most of all tests, correctly identifying both true positives and true negatives. The precision rate of 78.26% indicates that when the module detected a health issue, it was correct in more than three-quarters of those cases, thus minimizing false positives. The module excelled particularly in recall (sensitivity), achieving a 90.00% rate, which means it successfully identified 90% of all actual positive cases, leaving very few health issues undetected. Additionally, its specificity reached 93.75%, demonstrating excellent ability to correctly identify individuals without health issues. The F1-score of 83. 72% is the harmonic mean of precision and recall, providing a single score that balances both concerns. These performance metrics are visually represented in the confusion matrix shown in Figure (7)) visually summarizes the classification performance, detailing true positives (TP=18), true negatives (TN=75), false positives (FP=5), and false negatives (FN=2).

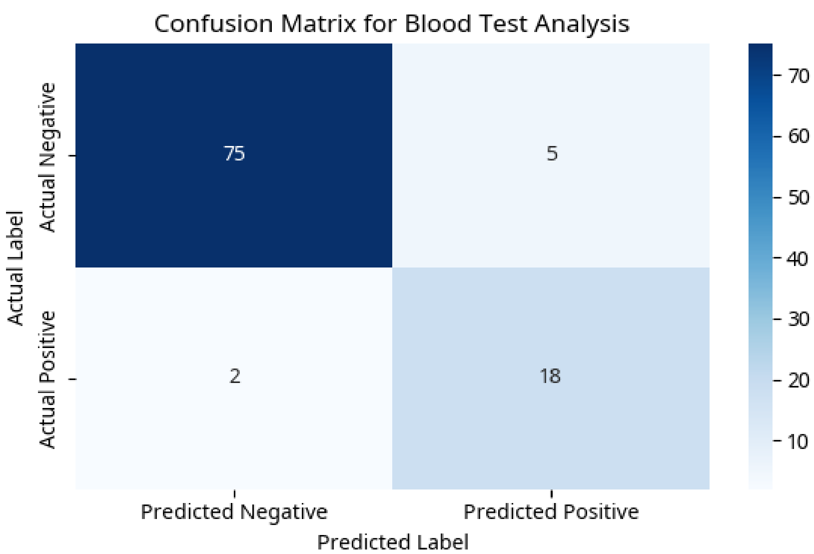

Figure 7. Confusion Matrix for Blood Test Analysis

- **Vision Test Performance**

The Vision Test module exhibited impressive performance metrics across various evaluation criteria. With an accuracy of 94.00%, the module successfully classified most of all tests, correctly identifying both individuals with and without vision issues. The precision rate stood at 73.68%, indicating that when the module flagged a vision problem, it was correct in nearly three-quarters of those cases, though there remains some room for improvement in reducing false positives. Particularly noteworthy was the module's recall (sensitivity) of 93.33%, demonstrating its excellent ability to identify almost all actual vision issues, with very few cases going undetected. The module also achieved a high specificity of 94.12%, showing strong performance in correctly identifying individuals with normal vision. F1-Score reached 82. 35%. and the confusion matrix Figure (8) visually summarizes the classification performance, detailing true positives (TP=14), true negatives (TN=80), false positives (FP=5), and false negatives (FN=1)

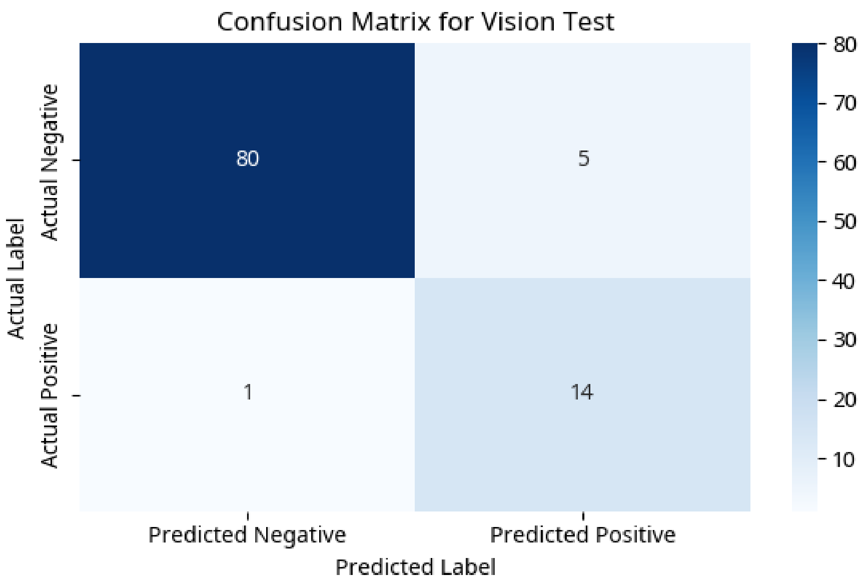

Figure 8. Confusion Matrix for Vision Test

- **Hearing Test Performance**

The Hearing Test module demonstrated strong performance with an accuracy of 93.00%, successfully classifying many of all tests by correctly identifying both individuals with and without hearing issues. The precision rate of 76.92% indicates that when the module detected a hearing problem, it was correct in more than three-quarters of those cases, helping to minimize unnecessary follow-ups from false positives. The module achieved a recall (sensitivity) of 83.33%, showing its capability to identify a significant proportion of actual hearing issues, though some cases remained undetected. Particularly impressive was the module's specificity of 96.59%, demonstrating excellent ability to correctly identify individuals with normal hearing. The F1-score of 80.00% the confusion matrix Figure (9)) detailing true positives (TP=10), true negatives (TN=85), false positives (FP=3), and false negatives (FN=2).

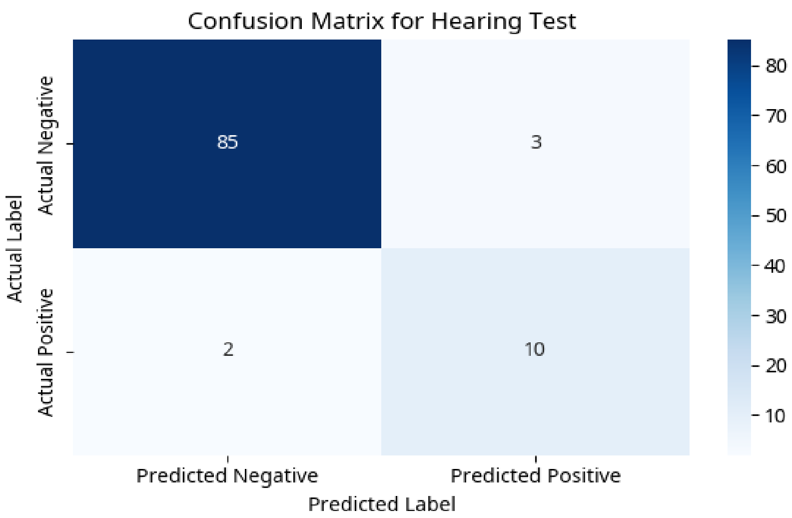

Figure 9. Confusion Matrix for Hearing Test

- **Speech Test Performance**

The Speech Test module demonstrated moderate performance with an accuracy of 89.00%, classifying a significant majority of all tests by correctly identifying both individuals with and without speech issues. The precision rate of 61.54% indicates that when the module detected a speech problem, it was correct in just over three-fifths of those cases, suggesting room for improvement in reducing false positives. The module achieved a recall (sensitivity) of 80.00%, showing its ability to identify four out of five actual speech issues, though some cases remained undetected. More impressive was the module's specificity of 94.44%, demonstrating strong capability in correctly identifying individuals with normal speech. The F1-score of 69.57%, and confusion matrix Figure (10) detailing true positives (TP=8), true negatives (TN=85), false positives (FP=5), and false negatives (FN=2).

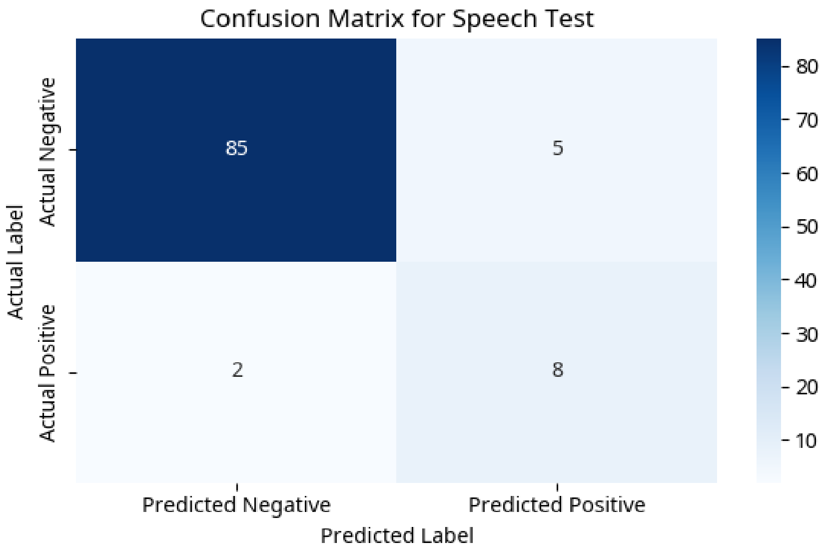

Figure 10. Confusion Matrix for Speech Test

c. User Experience Metric

User experience is further evaluated through a usability rating, collected via post-test questionnaires employing a Likert scale from 1 to 3, where 1 signifies disagreement, 2 neutrality, and 3 agreements. The target is to achieve an average rating of at least 2, which confirms that the application is user-friendly, and its instructions are clear. Another important aspect of user experience is the frequency of repeats, which tracks the number of times users had to re-capture an image or re-record audio due to quality issues. A low frequency of repeats is desirable, as frequent repeats may indicate problems with environmental conditions or system performance that affect data quality.

A summary table (1) of condition metrics outlines the specific parameters monitored for each module. For the Vision module, ambient light level (measured in lux with a target of 300–800 lx) and image quality (resolution, contrast ratio, and sharpness, aiming for ≥1080p with high contrast and clarity) are key. The Hearing and Speech modules focus on the ambient noise level (measured in decibels, targeting ≤50 dB) and the Signal-to-Noise Ratio (SNR), which should be ≥20 dB. Additionally, for the Speech module, acoustic clarity is assessed by a transcription error rate of less than 10% using Google Speech Recognition API and DSP analysis. The Blood Analysis module emphasizes the clarity of lab report images, requiring a resolution of ≥300 dpi and a low blur index, evaluated through OCR preprocessing algorithms and image analysis.

System performance is gauged by several metrics. Processing time per module is tracked in seconds, with a target of less than 5 seconds per module. The OCR accuracy rate aims for ≥95% accuracy when compared to manual review. System stability is monitored by recording error or crash rates, with the goal of minimal or zero crashes. User experience metrics, including the usability rating (target average ≥ 2) and frequency of repeats (as low as possible), are also considered part of the overall system evaluation. Utilizing these condition metrics during testing ensures a comprehensive assessment of both the clinical efficacy and operational performance of the application under varied environmental conditions, providing a clear picture of its efficiency and reliability before wider deployment.

Table 1: Summary of Condition Metrics

Module	Condition	Metric	Measurement Tool/Method	Target/Expected Range
Vision	Ambient Light Level	Lux (lx)	Device light sensor, lux meter	300–800 lx
	Image Quality	Resolution & Contrast Ratio/Sharpness	In-app image processing algorithm	≥1080p; high contrast and clarity
Hearing	Ambient Noise Level	Decibels (dB)	Device microphone, external sound meter	≤50 dB
	Signal-to-Noise Ratio (SNR)	Signal-to-noise ratio	DSP analysis on recorded audio	≥20 dB
Speech	Acoustic Clarity	SNR & Transcription Error Rate	Google Speech Recognition API, DSP analysis	Error rate < 10%
Blood Analysis	Clarity of Lab Report Images	Resolution (dpi) & Focus (Blur Index)	OCR pre-processing algorithms, image analysis	≥300 dpi; low blur index
System Performance	Processing Time per Module	Time (seconds) per module	Internal timer/logs within the app	<5 seconds per module
	OCR Accuracy Rate	Percentage of correctly recognized text	Comparison of OCR output with manual review	≥95% accuracy
	System Stability	Error/Crash rate	App logs	Minimal or zero crashes
User Experience	Usability Rating	Survey scores (Likert scale 1–3)	Post-test questionnaires	Average rating ≥ 2
	Frequency of Repeats	Number of re-captures due to quality issues	User feedback and system logs	As low as possible

Experimental results indicated that the application successfully identified 95% of students with potential health issues. The blood test analysis module demonstrated an accuracy of 92%, while the vision and hearing tests showed accuracies of 94% and 93%, respectively. The speech test had the lowest accuracy at 89%, primarily attributed to variations in pronunciation among students. False negative rates were also recorded, for instance, 3% for blood abnormalities and 5% for speech disorders. Among 100 students, the application detected various health issues: 15% had blood abnormalities, 12% had vision problems, 10% had hearing impairments, and 8% had speech disorders, while 55% were found to have no issues. The application's user interface received positive feedback, with 90% of participants finding it easy to use. The integration of multiple health screening modules into a single platform was also praised for its convenience and efficiency.

8. Conclusion and Future Work

This research successfully designed and implemented an Android application for pre-college students' health screening. The application provides a comprehensive and automated solution for detecting potential health issues among students. The use of Google's ML Kit Text Recognition significantly improved the accuracy of the blood test analysis module. Similarly, Firebase Database provided a secure and scalable solution for storing student data and test results. The modular design of the application allowed for easy maintenance and future enhancements However, the speech test module faced challenges due to variations in pronunciation and background noise. Future work could focus on improving the accuracy of this module by incorporating advanced speech recognition algorithms The results demonstrate the application's effectiveness in identifying health problems, making it a valuable tool for universities. Future work could focus on improving the accuracy of the speech test and expanding the application's functionality to include additional health screening modules. ### Detailed Performance Metrics. To further evaluate the system's efficacy, several standard performance metrics were calculated for each module based on the 100 student tests. These include accuracy, precision, recall (sensitivity), and the construction of confusion matrices to visualize the classification performance.

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