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A Visual Acuity Assessment System Based on Static Gesture Recognition and Naive Bayes Classifier

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ABSTRACT

Visual Acuity (VA) assessment is crucial for early vision screening, yet traditional methods are manual and time-consuming. Despite the advancements in human-computer interaction (HCI), there is no existing system fully addresses accuracy, efficiency and adaptability. This study introduces an intelligent VA assessment system that combines MediaPipe-based static gesture recognition with a novel Naive Bayes Classifier (NBC)-based VA Thresholds Determination (VATD) scheme. This integration offers a non-contact, user-friendly approach for rapid and precise VA testing. The VATD scheme is designed to significantly reduce the number of test trials; thereby, substantially improving the efficiency. Experimental validation confirms the system's high accuracy (96.72%) within a ± 0.1 deviation from standard methods, achieves a 68% reduction in test time compared to traditional methods, and offers a 27% efficiency improvement over ANN-based systems. This system promises to enhance VA assessments, particularly for children and adolescents, with its speed, accuracy, and broader applicability.

KEYWORDS

Human-Computer Interaction, MediaPipe, Naive Bayes Classifier, Static Gesture Recognition, Visual Acuity Assessment

INTRODUCTION

Visual acuity (VA) is a measure of the clarity and sharpness of an individual's vision (Fazeenah, 2021). The VA assessment plays a pivotal role in early vision screening (Samanta et al., 2023), especially among children and adolescents, allowing timely intervention to correct poor eye care habits and prevent further deterioration (Pindoria et al., 2024). In China, the VA test adheres to the standard GB/T 11533-2011, employing the tumbling E optotypes alongside the standard logarithmic vision chart. The chart utilizes a 5-mark recording system with 14 levels of VA, ranging from 4.0 to 5.3, with the standard testing distance set at 5 meters (Xian et al., 2023).

Current methods for assessing VA can be categorized as follows:

- Traditional method: This method employs paper eye charts and necessitates interaction between a physician and the subject (Claessens et al., 2023). Adhering to the line-by-line (LBL) method, the assessment begins with optotypes of the largest size which are gradually reduced in size until

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they are no longer discernible (Ng & Wong, 2022). Though cost-effective and widely accessible, it depends on the availability of trained professionals, leading to additional manpower costs and lower efficiency, which limits its potential for automation.
- Electronic screen display: The transition from paper-based charts to electronic displays, including computers, tablets, and smartphones, has facilitated the development of web-based and smartphone-based VA tests. The research conducted by Claessens et al. (2023), Gupta et al. (2023), and Min et al. (2024) supports the effectiveness of these methods, showing results that are comparable to the traditional paper-based approach. Despite the improved accuracy and the convenience of home testing, these methods essentially remain unchanged from the traditional approach; the reliance on manual interaction continues to be an obstacle for full automation and leads to low efficiency.
- Virtual reality (VR) integration: VR technology presents a novel avenue for VA testing, with Shen's team demonstrating high accuracy rates using VR cardboard and smartphones (Shen et al., 2022). However, the need for specialized VR equipment and its associated high costs limit its accessibility, particularly for home users (An, 2022).
- Human-computer interaction (HCI) technology: Recent advancements have introduced innovative VA testing approaches grounded in HCI technology, ranging from traditional keyboard input to modern techniques like gesture and speech recognition (Riedel et al., 2022). These methods facilitate automated and self-service VA assessments, reducing healthcare labor costs (Yu et al., 2016). However, opportunities for enhancing accuracy and efficiency within this domain persist, necessitating further refinement.

Current methods for VA assessment face various challenges, notably the necessity for low-cost and accessible devices to guarantee universal applicability. It is also essential to enhance accuracy through the computer technology in economically feasible devices. Moreover, it is critical to address the efficiency constraints inherent in traditional LBL approaches.

To meet these challenges, our study introduces an innovative intelligent VA assessment system integrating HCI technology with an effective scheme based on machine learning (ML). By incorporating ML into the HCI framework to refine LBL strategies, we anticipate a significant boost in testing efficiency. This system aims to simplify the VA testing process, providing a faster, more precise, and automated alternative to traditional methods, while also offering a low-cost and accessible solution for VA testing.

The main contributions of this study include:

- Development of a non-contact HCI system using readily available hardware, addressing high-cost device issues and enhancing system applicability.
- Implementation of MediaPipe-based static gesture recognition technology within the HCI system to enhance VA test accuracy.
- Utilization of response time data and an innovative scheme based on naive Bayes classifier (NBC) to increase testing efficiency.
- Collection of VA test data, training of the NBC model, and validation of the proposed system design through performance comparison experiments.

The paper is structured as follows: The next section outlines the advantages and disadvantages of traditional HCI methods applied in VA testing. This is followed by a section that delves into the design and architecture of our system and a section that evaluates the system's performance in terms of efficiency and accuracy. We then include a section that discusses the experimental results, emphasizing the innovations of our study and acknowledging its limitations. Finally, the concluding section summarizes the article and offers an outlook on future research.

RELATED WORK

In the dynamic field of VA assessment, recent advancements have focused on refining traditional testing methods, with a special emphasis on improving the modes of interaction. Historically, VA evaluations have relied heavily on direct interactions between humans. Despite their effectiveness, these traditional methods have faced limitations in terms of efficiency and precision. The advent of HCI technologies has led to the development of innovative approaches aimed at overcoming these obstacles. These methods, including both contact and non-contact forms of interaction, have significantly improved the assessment process. By facilitating the swift and precise collection of subjects' responses to optotypes, they effectively address the main limitations inherent in traditional testing paradigms (Modi & Singh, 2022).

Enhancements in Interaction Modalities

Touch-Based Interaction

A notable effort in this domain was contributed by Vafaie and Ahmadi Beni (2023), who advanced the use of a touch-based VA measurement system. This system integrates a wireless remote controller with a high-definition LCD screen, managed through a Raspberry-Pi mini-computer. This setup enables subjects to indicate optotype orientation through button presses on the remote controller. The primary advantage of this touch-based interaction modality lies in its potential to achieve a 100% accuracy in identifying optotype responses, provided the subjects will execute button interactions without errors. However, the reliance on button or keyboard inputs for signaling responses poses challenges, mainly because these inputs are less intuitive compared to verbal or gesture-based responses, potentially reducing the subjects' focus. Additionally, the shared usage of clinical equipment raises concerns regarding hygiene, necessitating enhanced maintenance efforts (Tseng & Sun, 2022).

Speech Interaction

In addressing the limitations associated with tactile methods for VA testing, research by Taufik and Hanafiah (2021) and Nasir et al. (2022) ventured into exploring non-contact modalities through the application of speech recognition technology.

Taufik and Hanafiah (2021) have developed an automated VA testing system that utilizes mel frequency cepstral coefficients and convolutional neural networks (CNN) for the accurate recognition of spoken digits. This method facilitates VA testing on conventional computing devices equipped with microphones and monitors, thus offering a practical alternative to traditional methodologies. The CNN model employed in their system demonstrated a commendable overall accuracy of 91.4%.

In a similar vein, Nisar's group has introduced an automated VA testing framework that leverages speech recognition to sidestep the limitations inherent to conventional ocular examinations (Nisar et al., 2022). This approach is particularly beneficial in regions with limited access to specialized eye care infrastructure. By employing an adaptive mel filter bank and weighted mel frequency cepstral coefficients for the extraction of speech features, their approach has achieved an overall accuracy of 91.875% when compared to expert ophthalmological evaluations.

However, despite the notable advantages of increased accessibility and efficiency brought about by these speech recognition-based methods, their accuracy and reliability can be significantly compromised by external factors such as background noise, accents, and variations in speech rate. The presence of environmental noise or concurrent speech further exacerbates these challenges, posing a threat to the dependability of such systems in acoustically demanding environments. These observations highlight the need for ongoing refinement and adaptation of speech recognition technologies to ensure their effective application in the field of VA testing.

Gestural Interaction

In response to the limitations observed in speech recognition, both Li et al. (2021) and Chiu et al. (2021) have explored the potential of gesture recognition as an alternative method. This approach signifies a strategic pivot towards more intuitive and user-friendly interaction modalities for VA assessment.

Li's team pioneered a self-administered VA testing program that capitalizes on dynamic gesture recognition technology, allowing individuals to perform VA tests in the comfort of their own homes (Li et al., 2021). This program, crafted by Python and OpenCV for image processing, interprets hand gestures captured through a built-in camera to adjust optotypes for precise VA evaluation. Despite its innovative design, the program's effectiveness in accurately recognizing gestures was documented at a success rate of only 75%. This may be due to the difficulty in identifying the starting and ending points of dynamic gestures, as well as the susceptibility to environmental interference during the target tracking process.

In a concerted effort to enhance gesture recognition accuracy, Chiu and colleagues have developed a cutting-edge hand motion recognition algorithm (Chiu et al., 2021). This algorithm employs 3-D hand data captured from an infrared camera, utilizing the leap motion device to identify specific hand movements. Notably, the algorithm demonstrates a high accuracy rate of 91.59% in distinguishing hand-waving motions. However, this approach is not without its challenges. The system occasionally encounters difficulties stemming from potential inaccuracies in gesture recognition, due to limitations inherent in the sensor technology, the ambiguity of certain hand gestures, and the variability in moving speeds among different users.

Incorporation of ML in VA Testing

Despite the focus on employing HCI technologies for capturing subjects' optotype responses, there has been limited exploration into the use of ML algorithms for swiftly determining VA thresholds. The predominant research approach has relied on the traditional LBL method, criticized for its inefficiency due to the extensive testing required at various VA levels. Chiu and his team have endeavored to optimize the VA testing process by employing artificial neural network (ANN) algorithms that leverage reaction times and hand motion recognition for VA estimation (Chiu et al., 2021). This strategy significantly improved the efficiency of VA testing. However, the applicability and generalizability of this approach are constrained, as it depends on data and interaction modalities specific to the specialized leap motion device, necessitating the availability of corresponding hardware for testing. Moreover, the need for such specialized equipment incurs additional costs and may limit the method's applicability in certain scenarios.

Upon a comprehensive review of the literature, it is evident that researchers tend to use advanced technologies to elevate VA testing in terms of accuracy, efficiency, and applicability. Yet, a method that seamlessly integrates these three facets remains elusive. Addressing this gap, our study introduces an innovative intelligent VA assessment system. It not only achieves superior accuracy and efficiency but also operates without the assistance of a physician, sidesteps the issue of excessive testing distances, and overcomes the inaccessibility of specialized equipment. Consequently, it is well-suited for extensive deployment in homes, communities, and schools.

SYSTEM DESIGN AND FRAMEWORK

HCI System Design Based on Static Gesture Recognition

System Framework Overview

Hardware Components. From the framework depicted in Figure 1, it is evident that our VA assessment system is fundamentally rooted in HCI design. The hardware components of the system consist of a system unit, display, camera, and speaker. The display component allows for a more flexible approach to presenting optotypes by replacing traditional paper-based eye charts (Xian et al., 2023). The system unit, camera, and speaker play analogous roles to a physician's brain, eyes, and mouth, respectively. This imitation allows the system to successfully swap out manual, time-consuming testing with automated, machine-driven alternatives.

Software Modules. Within the system unit, our HCI software is architecturally distinct, comprising specialized modules tailored for optotype display, gesture recognition, assistive functions, and flow control as shown in Figure 1. The flow control module systematically manages the VA testing process by working in coordination with other software modules and by following a predetermined VA testing workflow. It effectively manages the initiation, iteration, and conclusion of the VA testing process by executing the VA thresholds determination (VATD) scheme. Below is a detailed breakdown of the process:

1. Start the VA test by collecting essential parameters. Set the next VA level for testing, denoted as L_n^t, to 4.0. Activate the assistive function module and initiate the VA testing process.
2. Direct commands to the optotype display module to show the appropriate "E" optotype on the screen based on L_n^t.
3. Enable the camera for gesture image capture by sending commands to the gesture recognition module. Perform gesture recognition for each optotype and generate corresponding results. Route the results to the flow control module.
4. Upon receiving these results, the flow control module utilizes the VATD scheme to determine L_n^t and decide whether to proceed with or terminate the testing loop.
5. If the loop continues, repeat steps (2)–(4). Once the loop concludes, VA thresholds are set. Then, the actual VA is determined by applying the one level pass (OLP) criteria, which allows a maximum of five testing attempts for each level of optotype. A success rate of three out of five attempts is considered as a pass.

Introduction to MediaPipe

The static gesture recognition algorithms in use rely on the robust MediaPipe Hands module developed by Google. MediaPipe is an open-source framework and tool that offers a practical and effective solution for implementing gesture recognition across a wide range of applications (Lugaresi et al., 2019). A key component of MediaPipe is the MediaPipe Hands module that provides advanced capabilities for tracking hand and finger movements. By employing advanced algorithms, the MediaPipe Hands module accurately estimates the three-dimensional coordinates of 21 key landmark points on the hand from a single frame, as depicted in Figure 2 (Zhang et al., 2020). These landmark points include crucial areas such as fingertips, knuckles, and joints. The accurate estimation of these hand landmarks enables detailed analysis of hand movements and gestures, enhancing the system's ability to interpret and respond to user inputs.

Static Hand Gestures

This system utilizes static gestures for directional indication of the optotype, as depicted in Figure 3. When the testing begins but the optotype is not yet displayed on the screen, the subject's gesture is

Figure 1. VA Assessment System Framework Overview

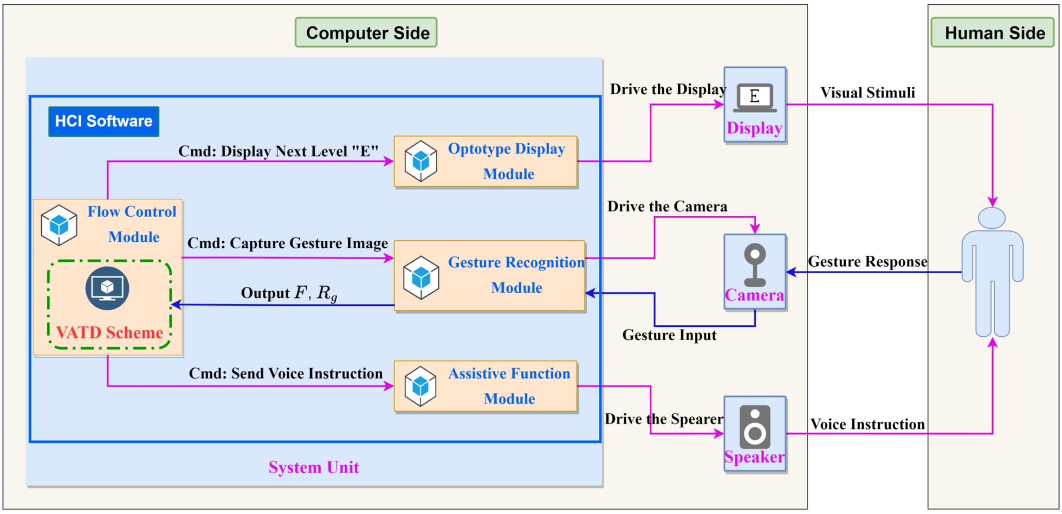
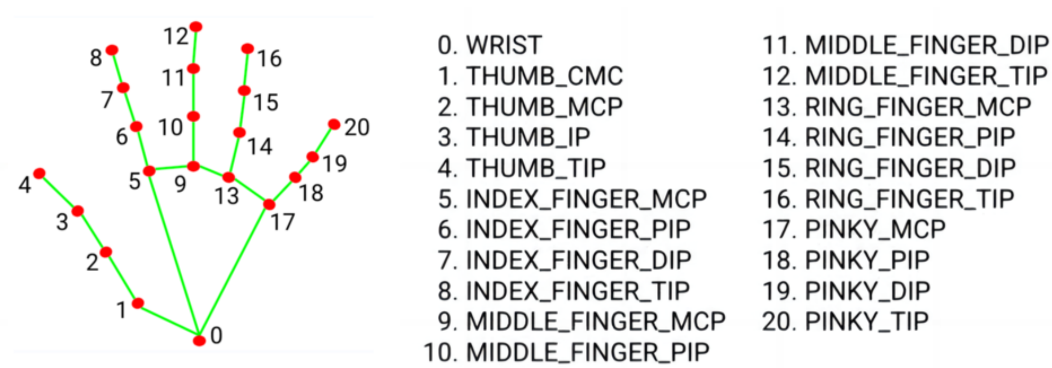


Figure 2. Hand Landmarks With 21 Joints (Note. Adapted from https://developers.google.com/mediapipe/solutions/vision/hand_landmarker)



in a ready state, symbolized by a clenched fist, as shown in Figure 3(a). Once the optotype appears, the subject makes a gesture pointing in the observed orientation of the optotype using their index finger, as shown in Figures 3(b)–3(e). After the recognition of the gesture for a single optotype is complete, the optotype is removed, and the subject's gesture returns into the ready state.

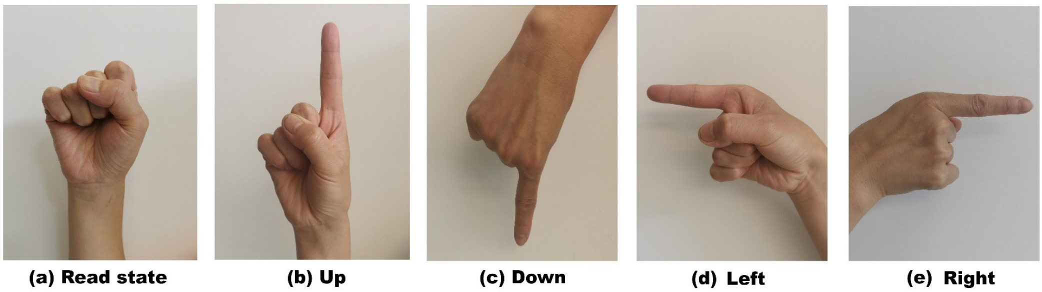
If a subject is unable to identify the orientation of the optotype, they should maintain a clenched fist gesture instead of randomly guessing a direction to point.

Single-Image Gesture Recognition

Recognizing a gesture from a single image involves a process known as single-image gesture recognition (single-image GR), which consists of three steps:

1. Hand detection: The image is inputted into the MediaPipe Hands module for detecting the hand. Only when a single hand is detected, does the process advance to the next step.
2. Index finger state determination: The state of the index finger, specifically whether it is open and straight, is evaluated. Four points on the index finger with indices 5, 6, 7, and 8 are extracted,

Figure 3. Static Hand Gestures for Optotype Orientation



denoted as (x_i, y_i), where i ranges from 5 to 8. Vector $\vec{\mathbf{v}}_1$ is created by connecting point 6 to point 7, with its direction from point 6 to point 7. Likewise, vector $\vec{\mathbf{v}}_2$ is formed by connecting point 7 to point 8, with its direction from point 7 to point 8. The distances d_i from the four finger points to the wrist point are calculated using the following formula:

$$d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{1}$$

Here, i ranges from 5 to 8 and (x_0, y_0) represents the coordinates of the wrist point with index 0. To consider a finger as straight, the angle θ_l between the two vectors $\vec{\mathbf{v}}_1$ and $\vec{\mathbf{v}}_2$ must be less than a predefined threshold θ_0. Additionally, to determine whether a finger is considered open, the distance from the fingertip to the wrist must be the maximum. If the conditions mentioned above are met, the process continues to the next step.

$$\begin{cases} \theta_l = \arccos\left(\dfrac{\vec{v}_1 . \vec{v}_2}{|\vec{v}_1| . |\vec{v}_2|}\right) < \theta_0 \\ \max\limits_{5 \le i \le 8} \{d_i\} = d_8 \end{cases} \tag{2}$$

3. Gesture direction determination: To determine the direction of the gesture, we first calculate the angle θ_x between vector $\vec{\mathbf{v}}_1$ and the unit vector $\vec{\mathbf{x}}$ along the positive x-axis. This angle helps distinguish whether the gesture is in the horizontal or vertical direction. Then, we consider the differences along the y-axis Δd_y and the x-axis Δd_x to determine the final direction. The values of these variables θ_x, Δd_y and Δd_x can be calculated using Formula (3).

$$\begin{cases} \theta_x = \arccos\left(\dfrac{\vec{v}_1 . \vec{x}}{|\vec{v}_1| . |\vec{x}|}\right) \\ \Delta d_y = y_7 - y_6 \\ \Delta d_x = x_7 - x_6 \end{cases} \tag{3}$$

If θ_x falls within the range of -45° to 45°, indicating a horizontal gesture, the sign of Δd_x determines whether the gesture is to the "Right" or "Left." For gestures outside this angular range, the sign of Δd_y dictates whether the motion is "Up" or "Down." The resulting gesture state S_g is an output that

Table 1. Algorithm: Gesture Direction Determination

Input: θ_x, Δd_y, Δd_x Output: S_g (gesture state)If $-45° < \theta_x < 45°$ thenIf $\Delta d_x > 0$ thenS_g = "Right" elseS_g = "Left" elseIf $\Delta d_y > 0$ thenS_g = "Up" elseS_g = "Down" return S_g

reflects the interpreted direction of the gesture. The algorithm below can be referred to for detailed information.

Single-Optotype Gesture Recognition

A complete single-optotype gesture recognition (single-optotype GR) process includes the recognition of all images captured during the transition from the ready state to the direction-pointing state, until the recognition termination criteria are met. This is achieved by using a series of single-image GR processes. The criteria for terminating recognition are designed to ensure both reliability and efficiency: the recognition concludes either when three consecutive images are identified as the same gesture (ensuring the stable gesture capture is less susceptible to interference) or when the duration surpasses a predefined limit (preventing prolonged inactivity by promptly terminating the process). The flow is visually depicted in Figure 4.

The result of the single-optotype GR includes two elements: the subject's response time T_r and the gesture matching result R_g (where 1 indicates "correct" and 0 denotes "incorrect"). In this context, T_r is measured from the moment when the optotype appears on the screen to the first detection of a directional gesture. Upon closely observing the VA testing process, we discerned certain patterns. It is consistent that subjects react promptly to clearly visible optotypes. Notably, within the critical threshold near the subjects' VA values, individuals spend extra time carefully examining the orientation of the optotypes, resulting in considerably longer response times (Heinrich et al., 2011). Given this, the response time T_r emerges as a crucial metric in estimating the true VA value.

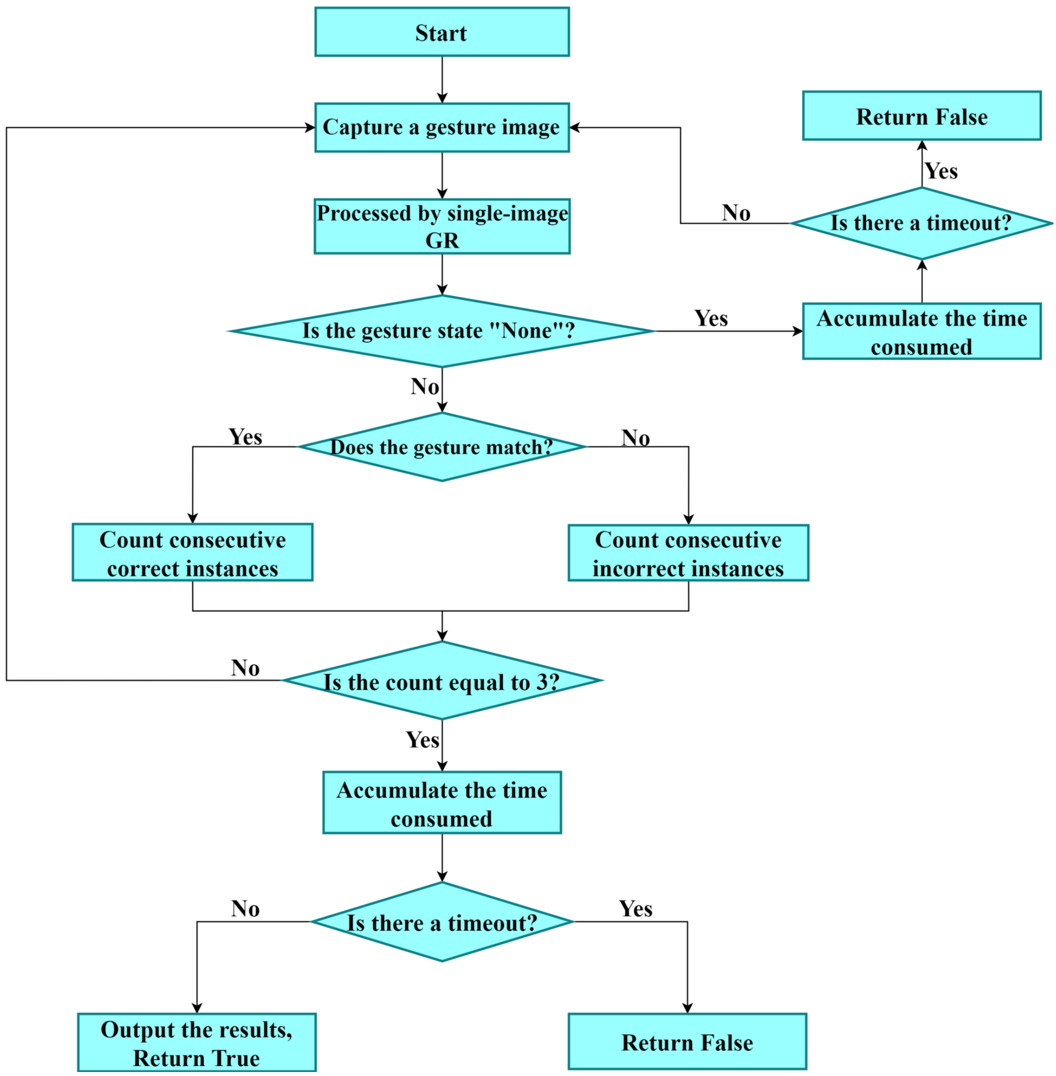
The dataset, comprising the current tested optotype level (VA level) L_c^t, the response time T_r, and the myopia status S_m (where myopia is denoted as 1 and the opposite as 0) manually input by the subject before the test, is consolidated into a feature vector, F. Following this, the F vector, in conjunction with R_g, serves as the output of the gesture recognition module and is relayed to the flow control module.

Scheme for Determination of VA Thresholds Based on NBC

In traditional VA testing methods, including those based on conventional HCI approaches, the determination of VA thresholds typically follows the LBL methodology. This process is both mechanical and time-consuming. In this section, we will explore the intelligent capabilities of our VA assessment system, the VATD scheme, which effectively bypasses the LBL method, reducing the number of tests required and improving the efficiency. It is noted that this is not a commonly addressed feature in most other systems.

A cornerstone of the VATD scheme is its focus on estimating true VA values. Therefore, it is of paramount importance to select the appropriate prediction model. In the realm of ML, classic classification methods such as support vector machine (SVM), ANN, and NBC are commonly employed. Among these, the NBC model stands out for its simplicity, efficient computation, stable classification performance, and its ability to handle multi-class classification problems. Notably, its suitability for small-sample data and incremental training scenarios makes it particularly appropriate for estimating VA values (Zhu et al., 2023). Furthermore, through the preliminary experimental

Figure 4. Flow of Single-Optotype Gesture Recognition



validation, NBC has demonstrated superior classification performance compared to SVM and ANN. Hence, the NBC model has been chosen for this study.

NBC Model

Let $X_S = [x_1^s, x_2^s, \ldots, x_n^s] \in R^{m \times n}$ represent the training sample dataset, where n is the number of samples and m is the dimension of the sample features. The corresponding label dataset, $Y_S = [y_1^s, y_2^s, \ldots, y_n^s] \in R^{1 \times n}$, consists of labels $y_i^s \in \omega$, where $\omega = \{\omega_1, \omega_1, \ldots, \omega_k\}$ represents the set of k classes. Each class ω_i has a prior probability $P(\omega_i)$. When considering a new and unknown sample $x = (x_1, x_2, \ldots, x_m)$, its conditional probability belonging to class ω_i is represented as $P\left(x \middle| \omega_i\right)$. By applying Bayes' theorem, we can calculate the posterior probability $P\left(\omega_i \middle| x\right)$ as follows:

$$P\left(\omega_i \middle| x\right) = \frac{P\left(x \middle| \omega_i\right) P(\omega_i)}{P(x)} \propto P\left(x \middle| \omega_i\right) P(\omega_i) \tag{4}$$

In the naive Bayes algorithm, it is assumed that the features $x_1, x_2, \ldots, x_m$ are independent of each other. This assumption allows us to transform the conditional probability $P\left(x \middle| \omega_i\right)$ as follows:

$$P\left(x \middle| \omega_i\right) = P\left((x_1, x_2, \ldots, x_m) \middle| \omega_i\right) = \prod_{j=1}^{m} P\left(x_j \middle| \omega_i\right) \tag{5}$$

Therefore, the NBC model can be represented as follows, where $H(\mathbf{x})$ represents the maximum *a posteriori* probability.

$$H(x) = \arg\max_{\omega_i \in \omega} \left\{ P(\omega_i) \prod_{j=1}^{m} P\left(x_j \middle| \omega_i\right) \right\} \tag{6}$$

For a continuous-valued feature, such as the dth feature taking the value x_d, given the class is ω_i and following a Gaussian distribution with a mean of $\mu_{\omega_i,d}$ and a variance of $\sigma^2_{\omega_i,d}$, the conditional probability density is described as follows:

$$P\left(x_d \middle| \omega_i\right) = \frac{1}{\sqrt{2\pi\sigma^2_{\omega_i,d}}} exp\left[-\frac{\left(x_d - \mu_{\omega_i,d}\right)^2}{2\sigma^2_{\omega_i,d}}\right] \tag{7}$$

To set up the initial NBC model, these detailed steps are followed:

1. Determining the feature attributes and class set: Select a feature vector $F = \left(L_c^t, T_r, S_m\right)$. In each collected sample $x = (x_1, x_2, x_3)$, the term x_i specifies the value of the ith feature, with y denoting the associated label value. The class set ω consists of 13 VA levels, ranging from 4.0 to 5.2.
2. Obtaining the training dataset: The experimental section can be referred to for detailed information.
3. Model training: The training data is fed into the NBC model to compute $P(\omega_i)$ and $P\left(x_j \middle| \omega_i\right)$. This computation helps generate the classifier. Gaussian density functions are employed to handle the continuous variables T_r.
4. Applying the classifier for estimation: Considering that the estimated VA value is always greater than the current VA level L_c^t being tested, our focus is to calculate $H(x)$ specifically for the cases that meet the condition $\omega_i > L_c^t$, as shown in the following equation:

$$H(x) = \arg\max_{\omega_i \in \omega \text{ and } \omega_i > L_c^t} \left\{ P(\omega_i) \prod_{j=1}^{3} P\left(x_j \middle| \omega_i\right) \right\} \tag{8}$$

The trained classifier (denoted as C in Equation [6]) is used to categorize the target data. For a given new sample x, if there is a $P\left(\omega_k \middle| x\right) = H(x)$, then x is categorized under class ω_k.

Updating the NBC Model With Incremental Learning

It is impractical to fully represent the overall distribution of VA levels with a limited training set. Therefore, it is crucial to adopt incremental learning to perform dynamic offline model updates. The introduction of incremental learning in updating the NBC model significantly enhances its adaptability and efficiency, particularly in dynamic data environments (Gu, 2023). This approach enables the model to dynamically adjust to new data patterns without the need for complete retraining, ensuring real-time data processing capabilities.

The main goal of this update is to improve the accuracy of model classification by establishing new values for $P^*(\omega_i)$, $P^*\left(x_j \middle| \omega_i\right)$, $n^*_{\omega_i}$ and n^*. This involves using prior information from the initial model and incorporating insights from newly added samples. Before the testing starts, subjects have the option to voluntarily input their true VA values. These values, when provided, cause samples from the system's testing process to be added to the new training dataset, X_{new}. The system periodically checks if X_{new} is populated when it is not engaged in testing tasks. If data is detected, the system triggers an offline model update task.

Suppose we have the current sample set X_S, consisting of a total of n samples, with n_{ω_i} representing the number of samples in class ω_i, for each new sample x_t in X_{new} with the label y_t, the classifier C updated by the following steps:

1. Update X_{new} by removing x_t.
2. Update X_S by adding x_t.
3. Adjust the classifier C based on the calculations specified in Formula (9).
4. Check whether X_{new} is empty. If it is empty, the update process is complete; otherwise, return to step 1 to continue the process for the remaining samples in X_{new}.

$$\begin{cases} P^*(\omega_i) = \begin{cases} \frac{n}{n+1} \cdot P(\omega_i) + \frac{1}{n+1} (y_t = \omega_i) \\ \frac{n}{n+1} \cdot P(\omega_i) (y_t \neq \omega_i) \end{cases} \\ P^*(x_j|\omega_i) = \begin{cases} \frac{n_{\omega_i}}{n_{\omega_i}+1} \cdot P(x_j|\omega_i) + \frac{1}{n_{\omega_i}+1} (y_t = \omega_i) \\ P(x_j|\omega_i) (y_t \neq \omega_i) \end{cases} \\ n^*_{\omega_i} = \begin{cases} n_{\omega_i} + 1 (y_t = \omega_i) \\ n_{\omega_i} (y_t \neq \omega_i) \end{cases} \\ n^* = n + 1 \end{cases} \tag{9}$$

VATD Scheme

The VATD scheme uses the NBC to quickly and accurately identify VA thresholds with fewer test trials, streamlining the assessment process and enhancing efficiency. The NBC model plays a key role in this scheme by generating an estimate to more effectively target VA thresholds. Detailed information about the VATD scheme is depicted in Figure 5. For a better grasp of the VA testing process within this scheme, it is essential to start by explaining the variables involved:

- R_g: The result of gesture matching.
- L_c^t: The current tested VA level.
- L_p^t: The previous tested VA level.
- L_n^t: The next VA level to be tested.
- L_c^e: The current estimated VA level.
- L_c: The set of levels for which testing has been completed with $R_g = 1$.
- L_{inc}: The set of levels for which testing has been completed with $R_g = 0$.
- Δl: The boundary difference, calculated as $\Delta l = \min\{L_{inc}\} - \max\{L_c\}$.
- ϵ: The spacing of VA thresholds.

In this scheme, two pivotal decision points come into play. Firstly, it is crucial to ascertain when the VA thresholds search process should be concluded. It depends on when the convergence condition is met, in particular, when $\Delta l = \epsilon$. Secondly, the determination of the next iteration's L_n^t depends on the value of R_g. When R_g equals 1, the feature vector F is transmitted to the NBC model, yielding the value of L_c^e. At this point, $L_n^t = L_c^e$. In cases where R_g is 0, the predictive power of the response time obtained from gesture recognition diminishes for the true value. Hence, the NBC model is bypassed, and the determination of L_n^t relies on both L_c^t and L_p^t. The final determination of L_n^t can be summarized by Formula (10).

$$L_n^t = R_g \times L_c^e + \left(1 - R_g\right) \times \left(L_p^t + \frac{\left(L_c^t - L_p^t\right)}{2}\right) \tag{10}$$

PERFORMANCE EVALUATION

Experimental Setup

Hardware Components

- Computer: The experiment uses a home computer with a screen resolution of 1,920 × 1,080 and a PPI of 96.
- Camera: A movable USB-connected camera with a resolution of 4 million pixels is selected for visual input during the experiment.

Eye Chart Requirements

- Optotype: E optotype with random orientations: up, down, left and right.
- VA reporting method: 5-mark recording system.
- Initial testing level: 4.0 (the largest size of the optotype).
- Testing distance: Based on the experiment's requirements, the available testing distance ranges from 2.0 to 5.0 meters, with a 0.5-meter increment between each option.
- Passing criteria: The OLP criteria are applied.

Testing Environment

The test is conducted indoors, with bright lighting to ensure optimal visibility. The camera should be placed at a distance of about 1 meter from the subject, aligned with the level of their hand gestures. Only one hand gesture will be permitted within the camera's field of view. The experiment will use the specific hand gestures depicted in Figure 3.

Experimental Subjects

A total of 100 subjects (200 eyes) were included in the study. Figure 6 depicts the VA distribution across 200 eyes of experimental subjects, with the y-axis indicating the number of eyes corresponding to each VA level.

Parameter Settings

The threshold θ_0 for gesture recognition was set at 15 degrees to balance the sensitivity and the stability of the algorithm. The NBC used Laplace smoothing (alpha=1) and calculated prior

Figure 5. Workflow for the VATD Scheme

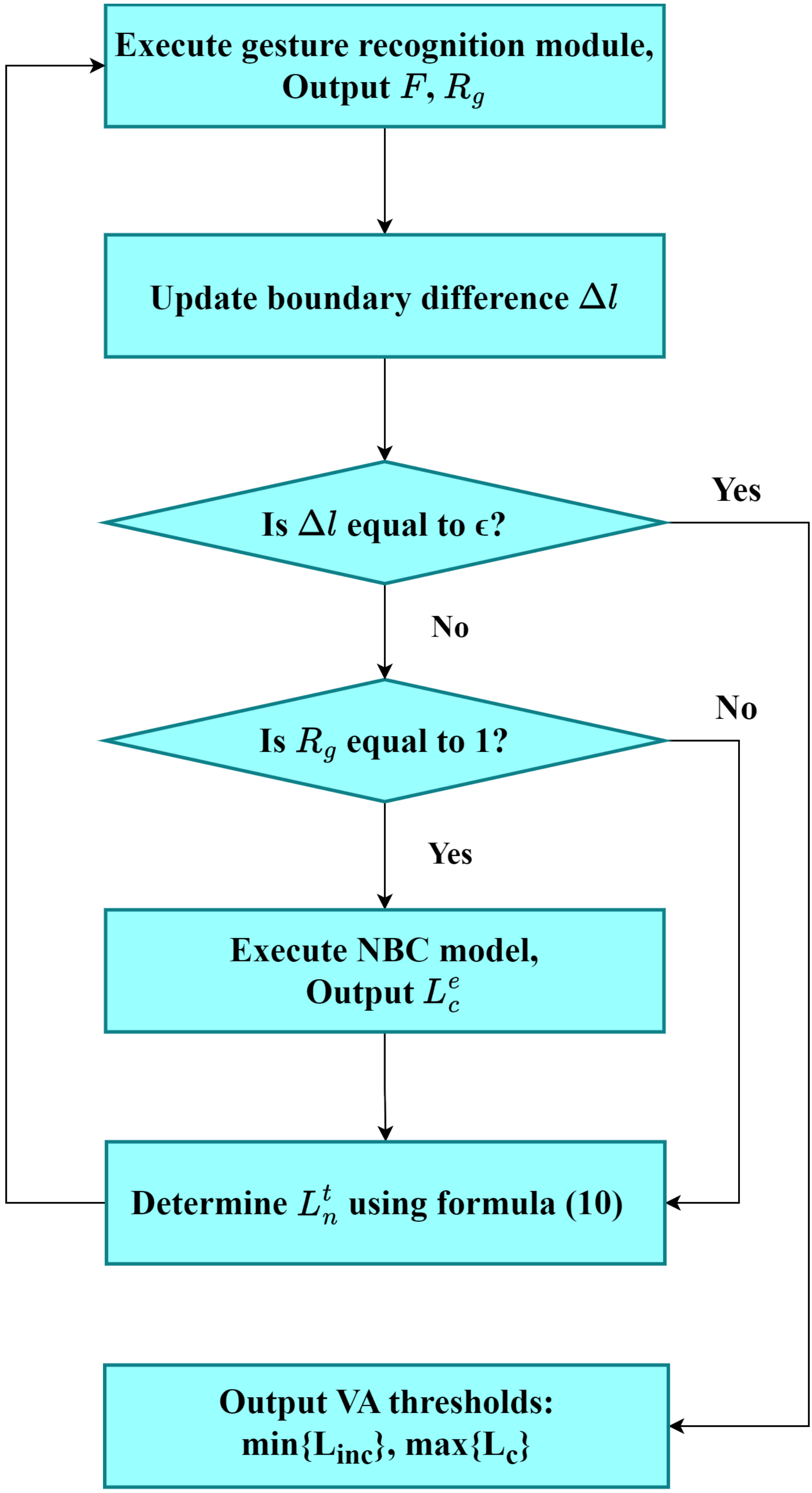
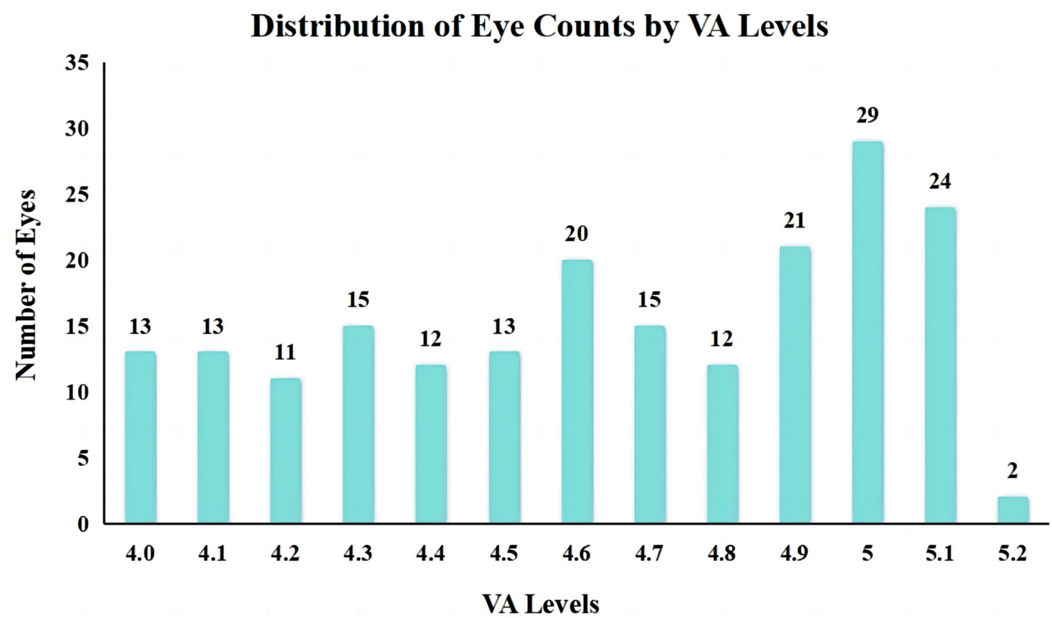


Figure 6. Distribution of VA Levels Among Experimental Subjects



probabilities automatically from training data. The ANN was structured as 3×10×1, with a learning rate of 0.001 and 200 iterations, employing ReLU activation to improve the learning efficiency. The SVM utilized an RBF kernel with a slack variable of 0.01 and underwent 200 iterations for optimal convergence and classification performance. Lastly, the spacing of VA thresholds ϵ in the VATD scheme was set at 0.1 to expedite the convergence of the VA search process.

Efficiency Evaluation Experiment

Experiment for Evaluating Output Errors of the NBC Model

In this experiment, data from 200 eyes underwent five rounds of VA testing, incorporating 13 levels of optotype assessments, yielding a total of 13,000 observations. Data points with inaccuracies were discarded, resulting in 7,405 valid observations. This dataset was split into training (80%) and testing (20%) sets. The objective was to evaluate the efficacy of three ML models—SVM, ANN and NBC—in predicting VA values. The models' performance was gauged by the discrepancy between the estimated and true VA values.

Figure 7 shows the error histogram for each model, where the x-axis represents the prediction error, and the y-axis indicates the number of instances (i.e., data points) at a given error level. It is evident from the figure that the bars for the NBC model are the tallest near zero error and become shorter as the error increases, indicating the NBC model's superior predictive performance.

Additionally, Table 2 provides a statistical analysis of the prediction accuracies within certain error bounds. It shows the NBC model's superior predictive capability, with accuracies of 91.02%, 96.98% and 99.47% for error bounds of 0.1, 0.2 and 0.3, respectively, outperforming both the ANN and SVM models.

Principle Verification Experiment of the VATD Scheme

The principle of the NBC-based VATD scheme was evaluated through the observation of a VA testing process for a randomly selected individual (actual VA value of 5.0). The VA test begins at the

Table 2. Percentage of Instances Within Specified Error Bounds for Different ML Models

ML Models	|Error| ≤0.1	|Error| ≤0.2	|Error| ≤0.3
SVM	85.67%	92.78%	98.00%
ANN	87.28%	94.27%	98.27%
NBC	91.02%	96.98%	99.47%

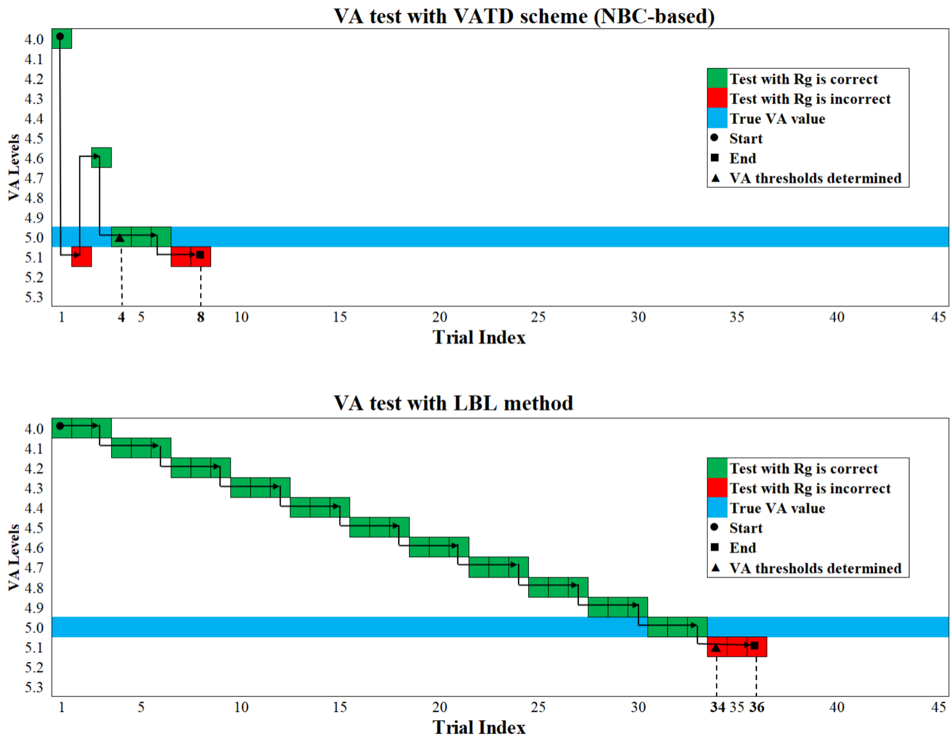
4.0 level. Through the application of the gesture recognition module, the system generates outputs for R_g and **F**. Given that R_g is assigned a value of 1, the **F** vector is subsequently fed into the NBC model, resulting in an estimated L_c^e value of 5.1. Remarkably, after just one trial, the predicted value closely aligns with the true VA value, within an error margin of only ± 0.1. Following this, L_c^e informs the determination of the next testing level, as per Formula (10), setting L_n^t at 5.1. Similarly, in the second test trial, L_n^t was directly determined by Formula (10) since the gesture recognition results at the level 5.1 indicated that R_g equaled 0, bypassing the NBC model. This iterative process continues until the convergence condition $\Delta l = \epsilon$ is met, efficiently ascertaining the VA thresholds for 5.0 and 5.1 in only 4 trials. After determining the VA thresholds, the OLP criteria is applied to both levels, necessitating an additional 4 trials for a total of 8. This methodology confirmed a final actual VA value of 5.0, whereas the traditional LBL method required 36 trials for the same determination. Figure 8 depicts the operational process of both methods, illustrating the VATD scheme's efficiency in reducing the number of necessary testing trials.

Real-World Efficiency Performance Evaluation

It is not statistically robust to test the VA of a single eye at a specific level. To address this, we randomly selected 62 eyes from 100 subjects, with VA levels ranging from 4.0 to 5.2. These eyes underwent VA testing using both the NBC-based and ANN-based VATD schemes, as well as the

Figure 7. Comparative Analysis of Classification Error Distributions Among Three ML Models

Figure 8. Performance Comparison Between VATD Scheme and LBL Method for an Individual Subject



traditional LBL method. The average number of trials conducted across different VA levels for each method was comprehensively recorded in Table 3.

Table 3 demonstrates that the NBC-based VATD scheme required the fewest number of trials for VA testing at both individual and all VA levels, with an average of 9.01 trials per eye among 62 tested eyes. This figure is significantly lower compared to the 12.32 trials required by the ANN-based VATD scheme and the 27.85 trials necessitated by the traditional LBL method. As a result, the NBC-based VATD scheme proves to be markedly more efficient, substantially reducing the number of required trials for testing. Given that the duration of each trial is roughly equal across the three systems, it can be inferred that the NBC-based VATD scheme has achieved a reduction of approximately 27% ((12.32 - 9.01) / 12.32) in testing duration compared to the ANN-based VATD scheme, and a reduction of 68% ((27.85 - 9.01) / 27.85) compared to the traditional LBL method.

Accuracy Evaluation Experiment

Accuracy Evaluation of Static Gesture Recognition

This experiment evaluated 100 subjects who performed tests using both their hands in four different directions: up, down, left and right. Each direction was tested 10 times, resulting in a total of 8,000 gesture recognition instances. Of these, 7,768 instances were correctly identified, leading to an overall accuracy rate of 97.1%. The results are presented in Table 4.

Accuracy Evaluation of the VA Test at Different Testing Distances

We conducted realistic experiments to assess the accuracy of the proposed intelligent VA test (iVAT) system, which utilizes HCI technology and the VATD scheme based on the NBC model.

Table 3. Average Trial Counts for VA Testing Using Different Mechanisms

VA Levels	Number of Eyes Tested	Average Trials (NBC-based VATD Scheme)	Average Trials (ANN-based VATD Scheme)	Average Trials (Traditional LBL Method)
4.0	5	8	12.2	7.2
4.1	5	8.6	12.4	10.6
4.2	5	9	12	14.2
4.3	5	9	12.6	18.4
4.4	5	9.2	12.4	21.2
4.5	5	9	12.2	25.8
4.6	5	9.2	12.6	28.6
4.7	5	9	12.4	31.4
4.8	5	9.2	12.2	35.8
4.9	5	9.2	12	38.6
5.0	5	9	12.4	40.8
5.1	5	9.2	12.2	44
5.2	2	9.5	12.5	45.5
All Levels	62	9.01	12.32	27.85

Table 4. Gesture Recognition Accuracy

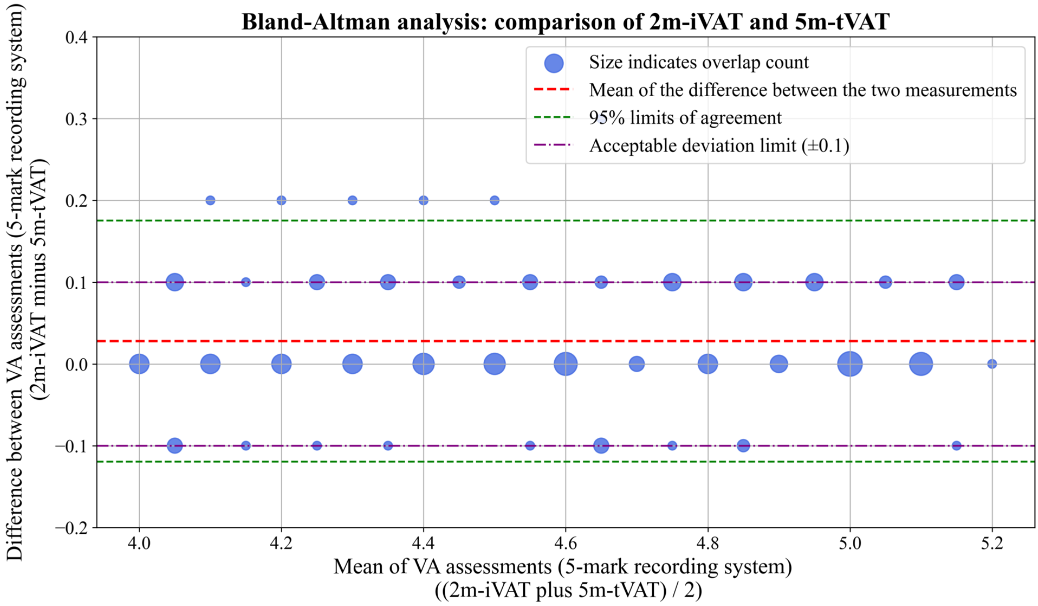
Direction	Gesture Collected	Correct Gesture	Accuracy
Up	2,000	1,984	99.2%
Down	2,000	1,958	97.9%
Left	2,000	1,916	95.8%
Right	2,000	1,910	95.5%
Overall	8,000	7,768	97.1%

For comparison, we also considered the results from the traditional VA test (tVAT) method used in national standards, which employs the human-human interaction approach with the LBL method.

The proposed iVAT system offers adjustable VA testing distances from 2 to 5 meters, setting it apart from the tVAT system which has a fixed testing distance of 5 meters. In order to assess the accuracy of the iVAT system, tests were conducted at both its minimum distance of 2 meters and its maximum of 5 meters. For this evaluation, 122 eyes were randomly selected from a total of 200 eyes and were subjected to three rounds of VA tests. Data was recorded using a standardized 5-mark recording system. The subsequent analysis included direct comparisons between the 2m-iVAT results and the 5m-tVAT, as well as a comparison of the results from 5m-iVAT and 5m-tVAT. To evaluate measurement congruence, the Bland-Altman analytical approach was adopted. This method, common in biomedical statistics, quantifies the mean difference between two measurements and delineates the 95% limits of agreement (95% LoA) (Bland & Altman, 2010).

Figures 9 and 10 clearly illustrate that the majority of data points are within the 95% LoA, with no evident trends, indicating high concordance between the iVAT and tVAT measurement methods. Furthermore, data from Table 5 show an almost zero mean difference, very low standard deviation, narrow LoA, and a high proportion of data points within these limits. These findings collectively

Figure 9. Bland-Altman Analysis of VA Tests: 2m-iVAT Versus 5m-tVAT



demonstrate that our VA assessment system is highly consistent with traditional testing methods, whether conducted at a distance of 2 meters or 5 meters; thereby, ensuring an exceptional accuracy in performance.

Figure 10. Bland-Altman Analysis of VA Tests: 5m-iVAT Versus 5m-tVAT

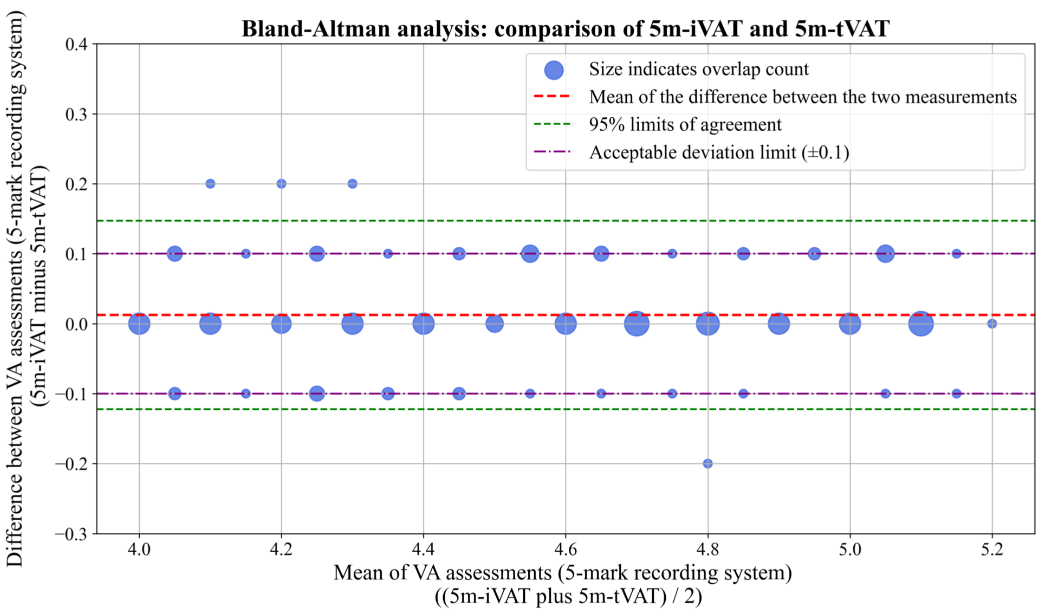


Table 5. Bland-Altman Analysis for Comparing Measurement Methods

Methods Comparison	Mean Difference	Standard Deviation	95% LoA
2m-iVAT vs 5m-tVAT	0.0279	0.0753	-0.1197 to 0.1755
5m-iVAT vs 5m-tVAT	0.0123	0.0687	-0.1224 to 0.1470

Table 6. Accuracy Rates of Different HCI Methods for VA Testing

Interaction Method	Accuracy Rate	Research Source
Dynamic Gesture	75.00%	Li et al., 2021
Speech Recognition	92.00%	Nisar et al., 2022
VR Interaction	92.86%	Riedel et al., 2022
Hand Motion	91.59%	Chiu et al., 2021
MediaPipe-based Static Gesture	97.10%	The study in this paper

DISCUSSION

Analysis of Experimental Results on Efficiency Evaluation

The efficiency enhancement in this study is primarily attributed to the proposed VATD scheme, centered around the NBC model. Comparative experiments among three ML models demonstrated that the NBC model offers superior predictive accuracy with limited sample sizes. Its capability for incremental learning in offline updates renders it highly suitable for VA testing scenarios. Nonetheless, estimating the true VA based on a single test highlighted the predictive accuracy limitations of the NBC model. Thus, the VATD scheme was developed on the foundation of the NBC model to prevent the divergence of the VA searching process due to significant output errors from NBC. The effectiveness of the VATD mechanism was validated through case analyses of the VA testing process and further confirmed by realistic VA tests on 62 eyes, showing that the NBC-based VATD mechanism outperforms traditional methods in efficiency on average. By leveraging the predictive results of NBC, the VATD mechanism rapidly converges to the true VA values of the test subjects, bypassing the inefficient row-by-row scanning of traditional LBL methods, significantly reducing the number of test trials required, and saving time. This substantial improvement in efficiency not only enhances user experience but also promotes the potential application of this method in large-scale automated testing scenarios.

Analysis of Experimental Results on Accuracy Evaluation

The data from Table 6 assesses the accuracy rates of various HCI methods used in VA testing, as discussed in related works. Compared to others, the static gesture recognition method based on MediaPipe currently exhibits the highest accuracy rate, underscoring the effectiveness of our algorithm. This success can be attributed partly to the precise hand landmark points provided by the MediaPipe Hands module and partly to the accurate recognition algorithm developed through geometric modeling analysis of gestures within the VA testing scenario. Verification through realistic VA tests at distances of 2 meters and 5 meters demonstrated a high congruence with the golden standard, with an accuracy rate within a deviation of ± 0.1 reaching 96.7%, illustrating the high accuracy of our VA testing system. The implementation of this non-contact, accurate gesture interaction system promotes the development of self-service and automated VA testing, facilitating the application of this method in settings beyond home environments, such as schools, communities, and shopping malls.

Innovations and Advantages of This Study

Traditional HCI technologies have primarily focused on addressing the accuracy of VA testing, with efficiency performance often being a bottleneck. The highlight of this study is the effective integration of the NBC-based VATD scheme within the framework of conventional HCI, offering not only an accurate VA testing process through static gesture interaction but also the leverage of gesture recognition response time and other critical data obtained during the interaction process to accelerate VA testing via the VATD scheme. Thus, compared to traditional manual testing and conventional HCI system testing, our system represents a qualitative leap in efficiency while maintaining a high accuracy rate.

From the analysis of our experimental results, the advantages of our research are evident in several key areas:

- Breaking efficiency barriers: The NBC-based VATD scheme bypasses the time-consuming traditional LBL method, significantly reducing testing time and enhancing user experience.
- Achieving high accuracy: By employing precise gesture recognition algorithms, our system provides a remarkably high accuracy rate for VA testing.
- Addressing accessibility challenges: The system requires only a standard computer equipped with a camera, making it easily accessible to the majority of household users.
- Adaptability to multiple scenarios: The convenience of gesture interaction, coupled with the system's efficiency and accuracy, enables its application in both self-service and automated testing environments, facilitating its adoption across various settings.

Limitations of This Study

While this study has achieved notable results, it also presents some limitations. One notable limitation is the system's dependency on manual parameter settings, which requires the researchers to have extensive experience and a deep understanding of the system's intricacies. Furthermore, the gesture recognition algorithm, based on a geometric model, encounters difficulties in environments with variable lighting conditions, backgrounds, and user behaviors. These challenges can cause a decrease in recognition accuracy and reliability, underscoring the need for robust algorithms capable of adapting to the dynamic conditions typical of real-world applications.

The NBC model, employed for its simplicity and efficiency, also presents areas for improvement. The current training dataset may not adequately capture the wide range of user VA levels, impacting the model's ability to generalize across different populations. The model's predictive accuracy could be further improved by expanding the dataset to include a more diverse set of VA measurements. Additionally, the trade-offs between model complexity, training time, and performance have yet to be fully explored. A more in-depth analysis could reveal optimizations that enhance the system's overall effectiveness without significantly increasing computational requirements.

CONCLUSION

In this study, we have developed an intelligent VA assessment system tailored for children and adolescents. This system integrates MediaPipe-based static gesture recognition with a novel NBC-based VATD scheme, establishing a non-contact HCI setup for VA testing. The proposed static gesture recognition algorithm enhances the system's accuracy, stability, and speed, offering users a swift, precise, self-administered, and convenient testing experience. A significant innovation of our system is the integration of the NBC-based VATD scheme within the HCI framework, introducing a higher level of intelligence to VA testing. This allows for ML-based precise predictions based on users' gesture response times, markedly reducing the number of test trials required. Comprehensive experimental validation demonstrates that our system achieves results with up to 96.72% accuracy within a ±0.1 deviation from standard testing methods. In efficiency terms, it substantially reduces detection time by about 68% compared to traditional VA testing methods and offers a 27% time saving over ANN-based systems. Consequently, our system distinguishes itself in accuracy, efficiency, and adaptability, promising an enhanced VA assessment experience for its users.

Acknowledging the system's limitations, it is suggested that two primary areas can be focused on in the future. First, improving gesture recognition will entail gathering a wide range of gesture data and refining algorithms to better accommodate the subtle differences in gestures, thereby significantly enhancing the system's adaptability and user-friendliness for a wider audience. Moreover, to increase the precision of VA predictions, we intend to expand the VA testing dataset and implement incremental learning strategies for updating the NBC model. The optimization of the model's size and efficiency shall also be prioritized to ensure stable and real-time performance across various application scenarios.

By continuing this line of research, we aim to provide a more intuitive, accessible, and effective tool for VA assessment to children and adolescents, aiding in the early detection and prevention of myopia in this young demographic. Additionally, this study strives to raise public awareness of vision care, encouraging societal engagement in the visual health protection of the youth.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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