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ROVAA: Offline attendance automation using a voice–OCR-based 3-DOF robotic arm with Raspberry Pi

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ABSTRACT

Conventional classroom attendance systems suffer from limitations in accuracy, hygiene, data privacy, and reliability in low-connectivity environments, whether they are manual, cloud-dependent, or single-modality systems. To address these gaps, this paper presents ROVAA, a low-cost, fully offline, AI-driven robotic attendance system in the classroom environment that uniquely integrates three complementary modalities: offline voice recognition, optical character recognition (OCR), and a 3- degrees of freedom (DOF) robotic arm controlled via inverse kinematics, an integration not demonstrated in prior work. The system operates on a Raspberry Pi 4 model B and employs the Vosk speech recognition model and Tesseract OCR for accurate offline processing. Audio and visual inputs are matched in real time to enable the arm to mark attendance at pre-calibrated positions on a touchscreen. Experimental validation under varied lighting and acoustic conditions yielded 96.2% speech recognition accuracy, 95.8% OCR accuracy, and 97.6% robotic arm precision, producing an overall system success rate of 92.8%, demonstrating that high reliability is achievable without cloud infrastructure. The system is designed for cost-effectiveness, data privacy, and scalability, making it suitable for resource-constrained environments such as rural schools and institutions with limited network access. It additionally serves as an educational platform for human–robot collaboration.

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1. INTRODUCTION

Robotics and automation are transforming the landscape of modern education. In college environments, robots are increasingly used not only for research and academic instruction but also in administrative and support roles. Laboratories and engineering departments regularly employ robotic arms, mobile robots, and autonomous platforms to teach concepts in embedded systems, mechatronics, artificial intelligence (AI), and control systems [1], [2]. These systems provide students with hands-on learning experiences and promote interdisciplinary collaboration. Robots are also utilized in project-based learning, robotics competitions, and innovation incubators, encouraging students to explore real-world applications such as industrial automation, assistive technology, and smart systems [3], [4].

Globally, the educational robotics market has experienced significant growth, with collaborative robotics (cobots) emerging as a leading trend. Cobots are designed to operate safely alongside humans, offering flexibility, adaptability, and cost-effectiveness compared to traditional industrial robots [5], [6]. In academic settings, cobots and educational robots have been increasingly integrated into classrooms to enhance engagement, provide interactive learning experiences, and support STEM education [7]. Studies suggest that approximately 25%–30% of educators worldwide are currently using educational robots or cobots in teaching, and adoption rates continue to rise as robotics becomes an essential part of modern curricula.

Collaborative robotics, or human–robot collaboration (HRC), represents a paradigm where humans and robots share workspaces and cooperate toward common objectives [8]. Unlike traditional robots that require isolation for safety, cobots incorporate sensors, AI-driven decision-making, and compliant mechanisms to enable safe, real-time interaction with humans [9]–[11]. In educational settings, this collaboration extends beyond instructional use to administrative tasks, improving efficiency and reliability.

Despite this progress, attendance tracking in academic environments remains a largely manual or cloud-dependent process. Manual entry is error-prone and unhygienic, while cloud-based or biometric systems require stable internet connectivity and raise concerns over data privacy - challenges that are particularly acute in resource-constrained or low-connectivity educational settings [11], [12]. Single-modality automated approaches, such as face recognition or radio frequency identification (RFID)-based systems, address some of these concerns but remain vulnerable to environmental variability and fail to provide a fully offline, privacy-preserving solution [13]. These limitations motivate the need for a robust, multimodal, and infrastructure-independent attendance automation framework.

Recent research in robotics and artificial intelligence has made considerable progress in the domains of human–robot interaction, visual recognition, and embedded control. Studies have presented low-cost robotic arm assistants based on platforms such as Niryo One for aiding mobility-impaired users, integrating voice interaction and machine vision for real-time object detection with over 96% accuracy [1]. Offline voice recognition frameworks using the Vosk engine [2] have been developed to enable robust, low-latency transcription without cloud dependency. Advanced inverse kinematics (IK) solutions have been proposed using deep learning methods such as IKFlow [14], while algorithmic modeling based on the Modified Denavit–Hartenberg (MDH) convention improves precision in kinematic parameterization [4]. Vision-based control and optical character recognition (OCR)-driven perception pipelines have also been explored for mobile robots and manipulators to achieve accurate localization, recognition, and navigation [13], [15].

This research contributes to the field by presenting a novel combination of embedded AI, computer vision, and robotic control for human–robot collaboration in educational administration. The scientific question addressed is: whether a low-cost, offline, and multimodal human–robot interaction system can automate manual attendance marking tasks with high reliability while operating on resource-constrained embedded hardware like the Raspberry Pi. The principal contributions of this work are as follows: i) Design and implementation of a low-cost 3- degrees of freedom (DOF) robotic arm that integrates offline voice and vision modules for autonomous attendance marking in a classroom environment, ii) inverse kinematics-based control algorithm that ensures precise stylus placement for reliable touchscreen interaction, iii) fully offline, self-contained HRC framework that fuses multimodal inputs (speech and OCR) in real time, preserving data privacy, maintaining reliability in the absence of network infrastructure, and iv) experimental validation under controlled and variable environmental conditions, achieving 96.2% speech recognition accuracy, 95.8% OCR accuracy, 97.6% robotic arm precision, and a 4-metric combined overall success rate of 92.8%.

The key finding that answers the scientific question posed above is that merging voice interaction, computer vision, and real-time robotic manipulation, the system achieves a 92.8% overall attendance-marking success rate under varied environmental conditions. Therefore, this study establishes a practical, affordable, and scalable model for intelligent human–robot collaboration in academic automation. The nature of the evidence we provide in support of this system is based on experimental validation under controlled and variable environmental conditions. In summary, the significance of these results lies in demonstrating that affordable, adaptable robotic systems can perform reliable real-world automation using low-cost embedded hardware. The system serves as a valuable platform for robotics education, human-robot collaboration, and accessible automation in resource-limited settings such as rural schools or small offices. More broadly, it offers a pathway for creating offline, privacy-preserving intelligent robots for non-industrial applications, primarily addressing a specific educational use case.

Robotics and automation are transforming the landscape of modern education. In college environments, robots are increasingly used not only for research and academic instruction but also in administrative and support roles. Laboratories and engineering departments regularly employ robotic arms, mobile robots, and recent research demonstrates rapid advancements in human–robot collaboration, AI-based control, and robotic arm systems, forming the foundation for the present study and research.

Recent advances in robotic manipulation increasingly emphasize multimodal human–robot interaction, vision-based control, and intelligent kinematic modeling. Voice interaction has emerged as a natural interface for robotic systems, particularly in assistive and collaborative settings. Early implementations demonstrated the feasibility of speech-controlled robotic arms using conventional speech recognition and embedded platforms, enabling basic manipulation tasks through predefined voice commands (Niryo-One robotic arm, modified the YOLO algorithm [1]), (Arm, Arduino controller, NRF sensor, and voice module [10]). Subsequent studies have focused on improving recognition accuracy and robustness by employing domain-adapted language models, with custom speech models shown to significantly enhance performance in constrained and offline environments (open-source Vosk Toolkit [2]), (speech processed on Android device, adaptive keyword spotting algorithm [11]).

Vision-based perception and control constitute another major research direction in robotic manipulation. Several works have explored image-based pick-and-place operations for low-degree-of-freedom manipulators using pattern recognition and object localization techniques [6], while more advanced visual servoing approaches have been proposed to maintain control stability even under actuator faults [16]. Recent developments incorporate deep learning architectures, including convolutional transformers and geometry-constrained learning frameworks, to improve perception-to-action mapping and convergence in visual servoing tasks (lite Transformer based visual encoder, unsupervised learning, and data augmentation [17]), (cerebellar model articulation controller (CMAC) [15]). Work that addresses robot-assisted student attendance in higher education classrooms, using AI-based face recognition is provided in [13].

Robotic kinematics, control, and motion planning remain central challenges, particularly for manipulators operating in dynamic or constrained spaces. Comprehensive reviews highlight the growing use of deep neural networks for inverse kinematics, obstacle-aware planning, and adaptive control in both structured and unstructured environments [3]. Alternative formulations based on modified Denavit–Hartenberg modelling and line geometry have been proposed to improve the robustness of kinematic representations [4], while metaheuristic and geometric approaches have been explored for trajectory generation and inverse kinematics in rigid and soft robotic systems [18] and [19] focusses on a multimodal interactive robot built with YOLOv8 object detection, cameras, and speech recognition, deployed in a real classroom with K-12 students to assist with physics lab tasks.

In parallel, human–robot collaboration has driven research in task sequencing, interaction safety, and environment awareness. Deep learning–based frameworks have been developed to control work sequences in collaborative assembly processes by adapting robot actions to human behavior [8]. Vision-based localization and obstacle avoidance techniques further enhance autonomous operation in urban and warehouse environments, ensuring safe navigation and effective collaboration with humans [9], [12]. Complementary perception tasks such as robust OCR for label recognition have also been addressed using vision–language models, supporting automation in industrial and service-oriented applications [20]. Interactive and intelligent robotic systems have additionally been demonstrated in structured human–robot engagement scenarios, such as collaborative game playing, highlighting advances in perception, decision-making, and interaction [21].

Collectively, these studies underline the importance of integrating speech, vision, and intelligent control for robust and intuitive robotic manipulation. However, many existing systems focus on isolated modalities or rely on cloud-based processing, motivating the need for low-cost, offline, and tightly integrated multimodal robotic frameworks—particularly for assistive and educational robotic applications.

Recent research in robotic systems has emphasized advances in perception, manipulator design, and human–robot collaboration (HRC), particularly for industrial and assistive applications. In the area of optical character recognition, deep-learning-based pipelines combining object detection and filtering mechanisms have demonstrated improved text localization and recognition accuracy in structured visual scenes [22]. Parallel efforts in robotic mechanism design have introduced novel 3-DOF manipulators, including parallel wrist–gripper assemblies and bio-inspired spherical robots, offering expanded singularity-free workspaces and improved interaction capabilities [23], [24]. Model-based design methodologies have been applied to higher-degree-of-freedom industrial robots to enhance precision, repeatability, and structural optimization [25].

Safety and adaptability remain critical considerations in physical human–robot interaction. Systematic reviews have examined contact modeling and impact measurement techniques to assess and improve safety in industrial HRC environments [26], while learning-based monitoring systems integrating vision and handheld devices have been proposed for real-time safety supervision in collaborative manufacturing [27]. Learning-driven interaction and adaptation have further been explored through collaborative manufacturing cells capable of acquiring interaction skills over time [28], as well as unsupervised and representation-learning approaches for object classification in HRC scenarios [29]. Beyond manipulation, advanced control strategies have been investigated for complex robotic platforms such as bipedal locomotion systems and assistive prosthetic devices, demonstrating the effectiveness of adaptive and nonlinear control methods in hazardous or human-centered environments [30], [31]. Broader studies in assistive robotics highlight the role of sensor fusion and machine learning in improving autonomy, usability, and interaction quality [32], [33].

There is growing work in educational robotics and offline-capable systems [34], [35]. The work in [36] proposes a human–robot collaborative teaching (HRCT) framework where robots assist teachers in classroom activities like social-emotional learning tasks, while [37] investigates the role of collaborative robots (cobots) in STEM labs, focusing on student–robot cooperation and task-based learning.

Differentiation of the present work: While existing studies predominantly target industrial collaboration, complex robotic mechanisms, or safety monitoring in manufacturing environments, the present work addresses a distinct and underexplored application domain—fully offline academic automation through autonomous attendance marking. Unlike OCR-centric approaches that focus solely on text detection and recognition [22], this work tightly integrates vision-based identification with real-time robotic manipulation to enable direct touchscreen interaction. In contrast to novel manipulator designs and high-DOF industrial robots [23]–[25], the proposed system deliberately adopts a low-cost 3-DOF arm optimized for precision stylus placement rather than mechanical complexity. Moreover, whereas many HRC frameworks rely on networked sensors, cloud-based intelligence, or safety supervision layers [27], [28], this study presents a self-contained, privacy-preserving multimodal system that fuses offline voice interaction, computer vision, and inverse-kinematics-driven control. By achieving a 92.8% attendance-marking success rate under varied classroom conditions, the work demonstrates a practical, scalable, and cost-effective HRC model that extends current research beyond industrial settings into real-world educational automation. Another key contribution is the system level integration of mechanical, electrical, electronics and software components.

2. RESEARCH METHOD

This section presents the methodology adopted for developing the AI-driven robotic attendance system. The approach integrates voice recognition, computer vision, and inverse-kinematics-based robotic control into a unified offline framework implemented on a Raspberry Pi 4 platform. The system is designed for cost efficiency, data privacy, and scalability in educational environments.

While prior studies often focus solely on robotic control or single-modality interaction, this work presents a multimodal human–robot interaction system that combines speech and text recognition with precise robotic actuation for a meaningful real-world task—attendance automation. Key differentiators include: i) Offline processing and HRC design: The system uses the Vosk speech model and Tesseract OCR, unlike typical cloud-dependent solutions. ii) Integrated multimodal interaction: Real-time fusion of audio and visual inputs guides robotic action, enhancing robustness. iii) 3-DOF inverse kinematics-based arm control: Offers higher precision over simpler, pre-programmed robotic systems in similar cost segments. iv) low hardware cost with high performance: Achieves 92.8% overall system accuracy using affordable components. v) Calibration GUI. vi) Educational and scalable design: The system doubles as a hands-on platform for learning about robotics, AI, and embedded systems.

2.1. System architecture

The proposed system follows a three-layer modular architecture comprising the input, processing, and actuation layers, as shown in Figure 1. In the input layer, two multimodal signals are acquired: i) Voice input through a Bluetooth microphone for spoken commands, and ii) Visual input from a camera for real-time OCR-based text detection on the touchscreen. The processing layer performs decision-making by matching the voice command with the detected text. When a valid match is found, the corresponding screen location is converted into spatial coordinates. Finally, in the actuation layer, a 3-DOF robotic arm performs the required tapping action through servo-controlled motion. This modular structure ensures robustness, scalability, and real-time responsiveness, while maintaining full offline operation.

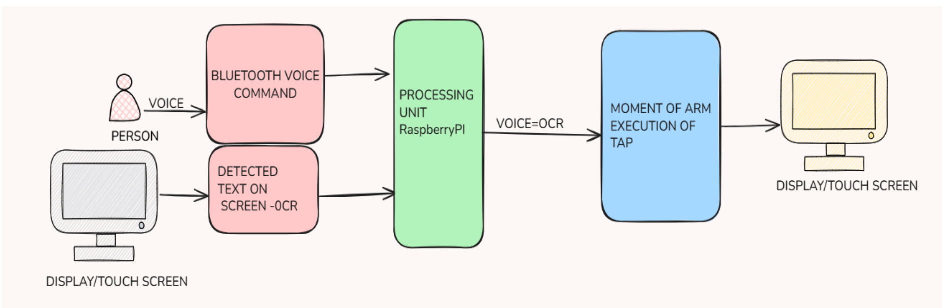


Figure 1. ROVAA system architecture

Figure 2 illustrates the human–robot collaboration attendance marking task, showing the interactive workflow between the human and the robotic system. The user speaks a student's name, which is captured through the Bluetooth microphone, while the camera simultaneously captures the touchscreen display. The system performs voice and text recognition to identify a matching name. Upon detecting a match, the robotic arm moves to the corresponding screen position, performs the tap action to mark attendance, and then waits for the next command.

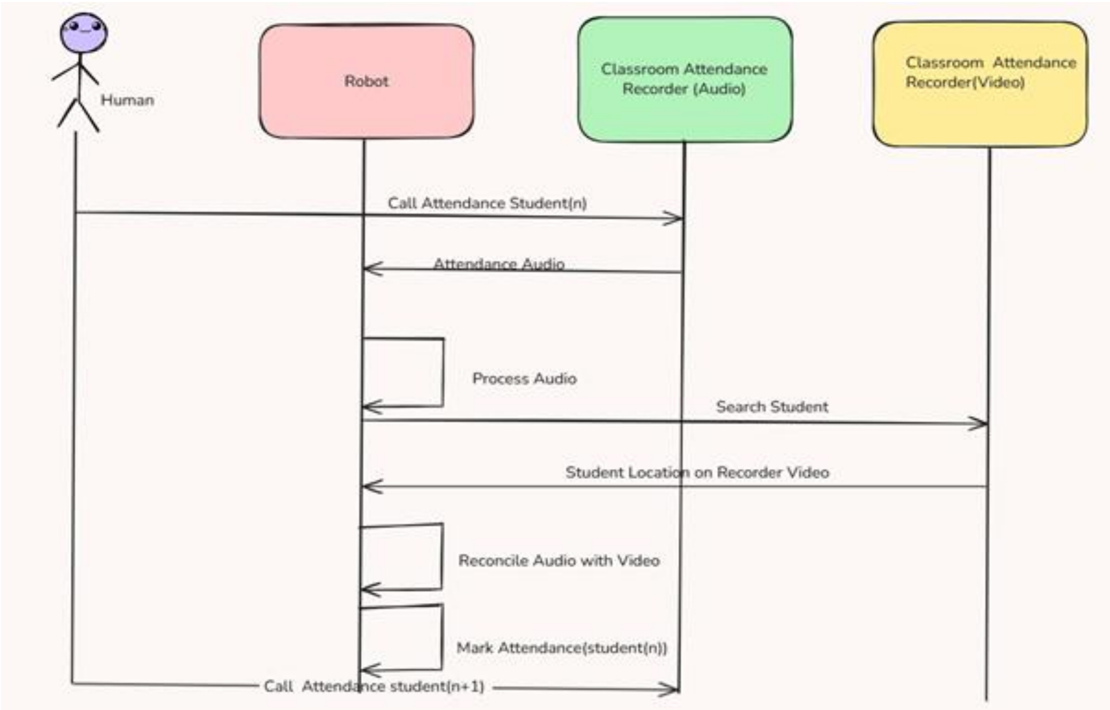


Figure 2. Human robot collaboration attendance marking task

A camera module mounted near the touchscreen captures visual data for OCR processing, while the stylus-based end-effector enables screen interaction. Power is supplied by a regulated DC source, ensuring stable operation during multi-servo movements. The complete hardware setup is shown in Figure 3, illustrating the physical structure and component interconnections.

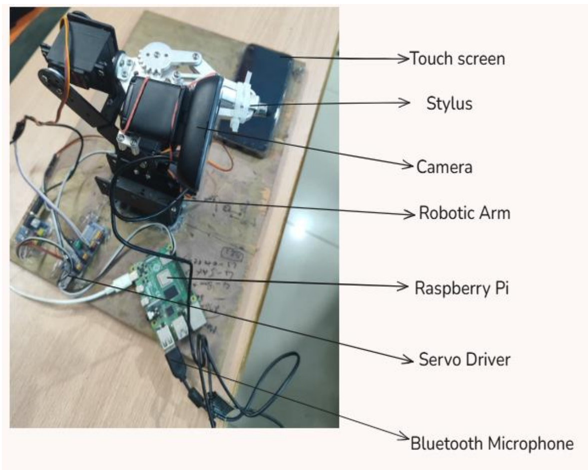


Figure 3. ROVAA hardware setup

2.2. Design rationale for robotic arm configuration

The choice of a 3-DOF robotic arm in the proposed ROVAA system is guided by task-specific requirements, cost constraints, and system simplicity

- Task-oriented sufficiency: The attendance automation task primarily involves planar positioning and controlled vertical motion. These actions require only three independent motions (X–Y positioning and Z-axis adjustment), making a 3-DOF configuration sufficient.
- Reduced system complexity: Compared to higher DOF systems (*e.g.*, 5-DOF or 6-DOF arms), a 3-DOF arm significantly reduces kinematic complexity, control overhead, and calibration effort.
- Improved reliability and stability: Fewer joints result in lower cumulative error propagation, increased structural rigidity, and more predictable motion—important for attendance marking.
- Cost and accessibility considerations: The system is designed as a low-cost, deployable educational solution. Higher DOF manipulators increase hardware cost, power, and maintenance.
- Offline operation compatibility: ROVAA operates in an offline environment, computational efficiency is critical. A 3-DOF system allows simpler inverse kinematics and control algorithms.

2.3. Hardware configuration

The hardware configuration is designed for affordability and functional reliability. The Raspberry Pi 4 (8 GB) serves as the central controller responsible for running the speech recognition, OCR, and robotic control modules. The robotic arm is a custom-built 3-DOF serial manipulator driven by three MG996R servo motors, chosen for their high torque and accuracy. These are controlled via a PCA9685 16-channel PWM driver, interfaced with the Raspberry Pi through the I^2C protocol for precise and synchronized motion control. A Tablet and smartphone were used to manifest the Display/Touchscreen.

2.4. Software framework

The software architecture is implemented as a multi-threaded control framework to achieve real-time operation. Each major function—voice recognition, OCR processing, and robotic arm control—is executed in an independent thread for parallel processing and reduced latency.

- Voice recognition: The system continuously listens for spoken input using the Vosk offline ASR engine, converting audio commands into text.
- OCR processing: The live camera feed is processed using Tesseract or EasyOCR to extract textual content from the touchscreen display.
- Matching and mapping: Once a match is found between the recognized speech and detected text, the corresponding pixel position is identified.
- Coordinate transformation: This pixel location is converted into real-world coordinates (x, y, z) using a pre-calibrated mapping system.
- Inverse kinematics computation: The control algorithm computes the joint angles $(\theta_1, \theta_2, \theta_3)$ for the base, shoulder, and elbow joints.
- Servo control: These angles are then converted to PWM signals and transmitted to the PCA9685 driver to control the servos.
- Reset: After completing the tapping action, the arm automatically returns to the home position $(90°, 90°, 90°)$.

The complete operational workflow is depicted in Figure 4, illustrating sequential data flow from input acquisition to robotic actuation. The voice and the camera inputs are simultaneously processed to provide a coordinated and synchronized system response. In order to provide a deterministic response and accurate positioning, the robot arm is returned to the home position after every single attendance marking task flow.

2.5. Cobot workspace mechanization

To ensure high precision in touchscreen interaction, a 5-point calibration system is implemented through the enhanced robotic arm controller GUI, as shown in Figure 5. During calibration, the robotic arm is manually aligned with five reference points on the touchscreen. Both screen pixel coordinates and corresponding real-world coordinates (X, Y, Z) are recorded. The system then interpolates between these points to establish a mapping function that converts detected text positions into robotic workspace coordinates. The GUI also provides: i) Manual servo control sliders for each joint. ii) Real-time display of joint angles and end-effector position (via forward kinematics), and iii) Options to save or load calibration data for repeatable sessions. This calibration significantly enhances positional accuracy and operational consistency during automated attendance marking.

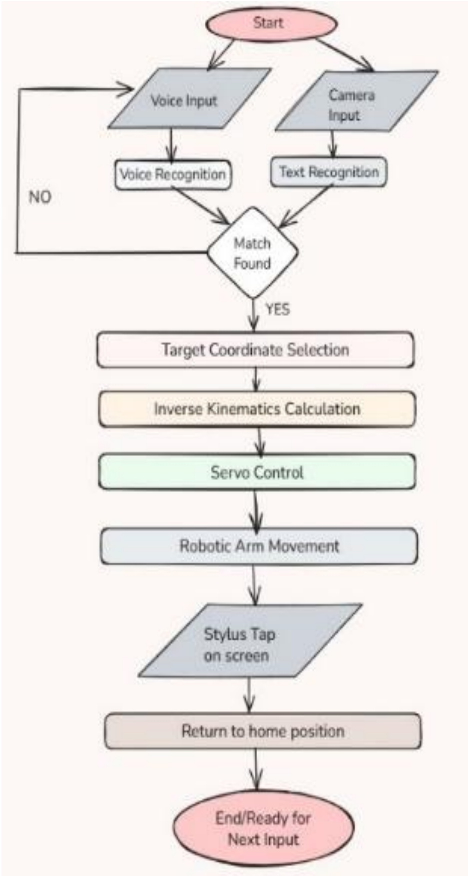


Figure 4. System operations flowchart

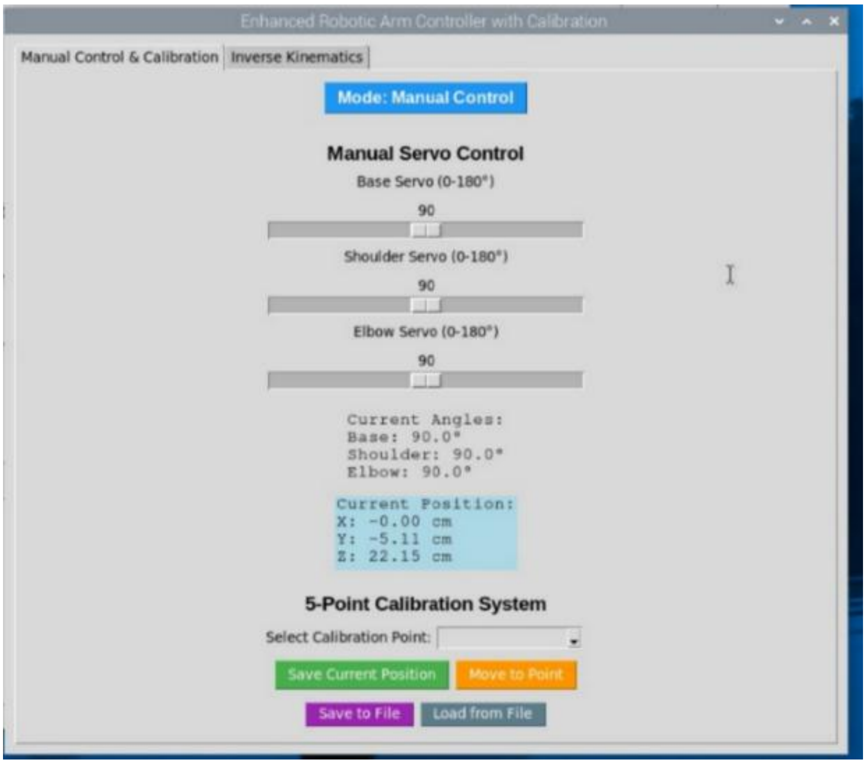


Figure 5. RA control calibration and inverse kinematics

2.6. Inverse kinematics-based control

The robotic arm's motion control is governed by inverse kinematics (IK), enabling the stylus to reach a desired three-dimensional coordinate (x, y, z)on the touchscreen. The manipulator is modeled using the Denavit–Hartenberg (D–H) convention, as shown in Figure 6, and its parameters are listed in Table 1.

The parameters in Table 1 are delineated as follows: L_1 = 3.5 cm is the vertical offset from the base to the shoulder joint, L_2 = 11.0 cm is the shoulder-to-elbow link length, and L_3 = 15.9 cm is the elbow-to-stylus link length. The computed joint angles are then translated into PWM control signals via the PCA9685 driver using the Adafruit PCA9685 library. Each servo receives calibrated pulses within the 500–2500 µs range for smooth actuation. Safety measures—such as angle constraints, motion sequencing, and emergency stop routines ensure reliable and repeatable operation.

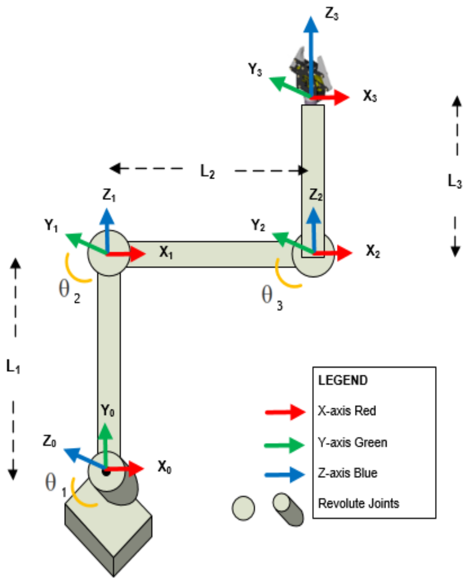


Figure 6. Kinematic model of RA

Table 1. DH convention table

Joint	θ_i (Variable)	d_i (link offset)	a_i (link length)	α_i (link twist)
1	θ_1	L_1	0	90°
2	θ_2	0	L_2	0°
3	θ_3	0	L_3	0°

The inverse kinematics of the 3-DOF arm is derived to compute the joint angles $(\theta_1, \theta_2, \theta_3)$ required for a desired end-effector position (x, y, z). The equations are provided as:

– Base joint angle

$$\theta_1 = \tan^{-1}(\frac{y}{x}) \tag{1}$$

where x and y are the coordinates of the end-effector (EE) in the horizontal plane.

– Radial distance and effective height

$$r = \sqrt{x^2 + y^2} \tag{2}$$

$$z_{\text{eff}} = z - L_1 \tag{3}$$

where z_{eff} is the height of the end-effector relative to the shoulder joint, and z is the coordinate of the EE.

– Intermediate term for elbow angle computation

$$D = \frac{r^2 + z_{\text{eff}}^2 - L_2^2 - L_3^2}{2L_2L_3} \tag{4}$$

– Elbow joint angle

$$\theta_3 = cos^1(D) \tag{5}$$

– Shoulder joint angle

$$\theta_2 = \tan^{-1}(\frac{z_{\text{eff}}}{r}) - \tan^{-1}(\frac{L_3 \sin\theta_3}{L_2 + L_3 \cos\theta_3}) \tag{6}$$

In addition to the analytical inverse kinematics equations, several control considerations are incorporated to ensure reliable and accurate operation of the 3DOF robotic arm. Before computing the joint angles, a workspace feasibility check is performed to confirm that the desired coordinate (x, y, z) lies within the manipulator's reachable region. The reachability condition $(L_2 - L_3)^2 \leq r^2 + z_{\text{eff}}^2 \leq (L_2 + L_3)^2$is evaluated, and any violation triggers a safe abort to prevent mechanical overextension. The IK solution also produces two possible configurations—commonly referred to as elbow-up and elbow-down—and the controller automatically selects the configuration that satisfies joint limits while minimizing the overall change from the arm's current pose. This improves motion smoothness and reduces unnecessary servo actuation.

To enhance numerical stability, the IK solver employs an atan2-based formulation for the elbow angle, avoiding the discontinuities associated with the direct $\cos^{-1}(D)$ computation. Singularities, such as those occurring when the radial distance r approaches zero or when the arm is fully stretched, are detected and managed by constraining the solution space and retaining the previous valid joint state whenever necessary. Furthermore, each joint is assigned experimentally determined angle limits to prevent the stylus or arm links from colliding with the touchscreen or exceeding the physical capabilities of the MG996R servos.

Once valid joint angles are obtained, they are mapped to servo commands using a calibrated linear PWM-conversion model. Each servo is assigned a pulse window between 500–2500 µs, with individualized offsets corresponding to its mechanical zero position. This calibration ensures that the computed angles precisely match the stylus trajectory on the touchscreen. To improve motion quality, commands are executed using a smooth trapezoidal motion profile rather than abrupt angular jumps, allowing gradual acceleration and deceleration that reduce vibration, overshoot, and servo load.

Finally, the IK-based control loop includes several safety mechanisms, including continuous validation of computed angles, detection of invalid or undefined states, and an emergency stop procedure that immediately disables the PCA9685 outputs. A predefined home position enables safe initialization and recovery.

2.7. System advantages

The proposed architecture achieves complete offline operation, minimizing dependency on cloud services [38] while ensuring data privacy and low latency. Its modular design allows individual components—such as the OCR module, microphone, or arm controller—to be independently upgraded. This methodology enables a cost-effective, real-time, and scalable robotic attendance solution, adaptable to other applications such as automated digital signing, classroom interaction, or assistive educational robotics.

2.8. Reproducibility

To enable full replication of the proposed attendance automation system, this section provides complete details of the hardware configuration, software environment, and calibration procedure used in the implementation. The system is built on a Raspberry Pi 4 Model B (8 GB RAM) serving as the primary controller, interfaced with a PCA9685 16-channel PWM servo driver to operate three MG996R metal-gear servo motors that form the 3-DOF robotic arm. A Raspberry Pi Camera Module (v2 8 MP or HQ variant) captures real-time visual data for OCR processing, while the end-effector is equipped with a capacitive stylus for precise touchscreen interaction. Voice commands are acquired using a Bluetooth microphone or EarPods, specifically tested with the Boat Airdopes 121v2, and all components are powered using a regulated 5 V, 3 A DC supply. The touchscreen attendance interface used during experiments was displayed on a Lenovo Tab M10 FHD 10.1-inch tablet and a Realme 6 smart phone was also used in some experiments.

The software stack consists of Raspberry Pi OS (64-bit, Bookworm) running Python 3.9, with Vosk's offline ASR model (vosk-model-small-en-us-0.15) for speech recognition and Tesseract OCR Engine version 5.3.0, accessed through the Pytesseract 0.3.10 wrapper, for text extraction. Additional dependencies include OpenCV 4.6.0 for image processing, the Adafruit PCA9685 Python library (v1.0.1) for servo control, NumPy 1.24 for numerical computation, and multi-threaded execution implemented using Python's standard threading module to achieve real-time operation.

A five-point calibration method was used to establish the mapping between screen pixel locations and the robotic arm's workspace. During calibration, the arm was manually aligned with five reference points on the touchscreen, and the corresponding pixel coordinates (x_s, y_s) and physical coordinates (X, Y, Z) were stored in a calibration file (calib.json). The system then applied linear or bilinear interpolation to convert detected OCR positions into robotic arm coordinates. This calibration yielded a mapping accuracy of approximately ±0.5 to 1.0 cm and was repeated prior to each experiment to ensure consistency. These detailed specifications provide a blueprint for re-implementing the proposed system in academic and research environments.

3. RESULTS AND ANALYSIS

The proposed AI-driven robotic arm attendance system was experimentally evaluated to verify its performance, accuracy, and response time under real classroom conditions. The experiments were conducted using a Raspberry Pi 4-based setup, where each module—voice recognition, OCR detection, and inverse kinematics (IK) control—was tested individually and in an integrated manner. The voice recognition module, implemented using the Vosk offline speech engine, achieved an accuracy of 96.2%, effectively detecting user commands despite moderate background noise. This robustness demonstrates the suitability of the system for typical classroom environments.

The OCR module, developed using Tesseract, obtained an average accuracy of 95.8% under standard lighting, with a slight decrease in performance during glare or partial obstruction. Together, these modules ensure high confidence in command-text correspondence, a key factor in preventing false triggering. The 3-DOF robotic arm achieved sufficient precision in touchscreen tapping through inverse kinematics-based control. Calibration experiments confirmed a pointing error of less than 1 cm, which was adequate for reliable interaction with standard touchscreen interfaces. The average cycle time per attendance entry was 4.3 seconds, representing efficient end-to-end task execution from command recognition to robotic actuation.

The integrated multimodal design, combining both auditory and visual inputs, significantly improved reliability by enforcing a dual-confirmation mechanism—a command was executed only if both speech and OCR results matched. A summary of the system's performance metrics is provided in Table 2. Data for calculations are obtained from Table 3 experimental test trial data. The module accuracies are calculated:

$$\begin{aligned}
&Voice\ Accuracy = (Total\ Voice\ success/Total\ No.of\ samples)\\
&\qquad = (96+96+96+96+97)/500 \ = \ 96.2\%\\
&OCR + Matching\ Accuracy = (Total\ OCR + M\ Success/Total\ No.of\ samples)\\
&\qquad = (96+95+97+95+96)/500 = \ 95.80\%\\
&IK\ Accuracy = (Total\ IK\ success/Total\ No.of\ samples) = (97+97+97+98+99)\ /\ 500\\
&\qquad = \ 97.60\%
\end{aligned}$$

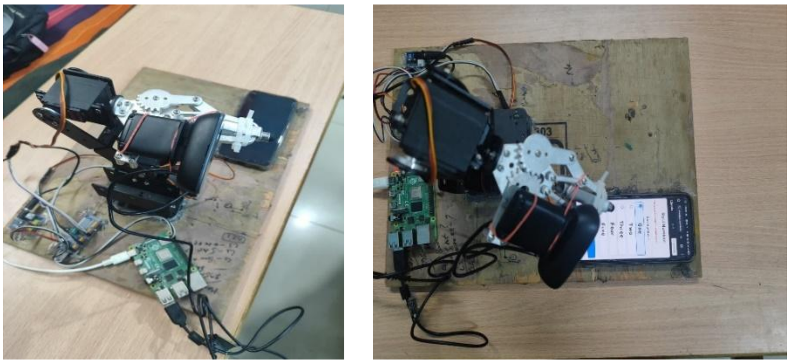
Table 2. Performance metrics of the proposed system

Metric	Proposed system
Voice recognition accuracy	96.2%
OCR accuracy	95.8%
IK Accuracy	97.6%
Robotic arm pointing error	< 1 cm
Overall system success rate	92.8%
Cycle time per entry	~4.3 seconds

Table 3. ROVAA test data from experimental trials

Trial	Voice-only fail	OCR-matching only fail	IK-only fail	Voice–OCR overlap fail	Voice–IK overlap fail	OCR–IK overlap fail	Total failures	Overall success (%)
Trial 1(100)	2	2	1	1	1	1	8	92
Trial 2(100)	1	2	1	2	1	1	8	92
Trial 3(100)	2	1	1	1	1	1	7	93
Trial 4 (100)	1	2	0	2	1	1	7	93
Trial 5(100)	2	2	0	1	1	0	6	94
Category Fail	8	9	3	7	5	4	36	
Average								92.8
Std. Dev.								0.75

Figure 7 illustrates the robotic arm during the attendance-marking operation. In Figure 7(a), the arm is shown at its calibrated home position, while Figure 7(b) shows the arm executing a touchscreen tap at the detected coordinate corresponding to the validated command. These demonstrate precise stylus movement and repeatable task performance.



(a) (b)

Figure 7. Robotic ARM (RA) poses (a) RA at home position before task and (b) RA using touchscreen - attendance marking

To enhance system transparency and educational usability, a human–robot collaboration (HRC) Dashboard was developed, as depicted in Figure 8. This dashboard unifies real-time monitoring of all modules, displaying system status, valid command lists, and module activity indicators. The Dashboard's central panel visualizes the synchronization between voice and OCR detections, showing confirmed matches in the "Recent Matches" window. Additional features, such as command history and performance metrics, provide users with operational insights, while the simulation and control tools allow system resets, test injections, and log saving. The interface not only simplifies system interaction but also serves as an educational visualization tool, demonstrating the integration between perception (voice + vision) and robotic control. It supports modular testing, debugging, and live classroom demonstrations, making it suitable for academic and research environments. A comparative performance evaluation with existing robotic systems is summarized in Table 4.

Figure 8. HRC dashboard

Table 4. Comparative analysis of robotic systems

Metric	Zhang *et al.* [15]	Budagov *et al.* [13]	Guo *et al.* [17]	Latif *et al.* [19]	Cui *et al.* [22]	Proposed system
System approach	Neural network (CMAC)	Robot + face recognition (AI-assisted)	Transformer + RL	YOLOv8 + Speech recognition + LLM (MM)	YOLO + PaddleOCR	Multimodal (Voice, OCR, IK)
Application	Visual Serving	Classroom attendance (HE)	Simulated manipulation	Classroom lab assistant (K-12)	OCR in logistics	Classroom attendance
Precision	–	-	–	–	–	< 1 cm
Accuracy	Robust	High (face recognition)	92%	~75%	89.5%	92.8%
Efficiency/ speed	Fast learning	Real-time	Moderate	1.64 s	76 FPS	4.3 s
Robot DOF	6	Social/mobile robot	Simulated	Low-DOF servo	–	3
Hardware/ Cost	High	Low–moderate	Moderate	Low	High	Low
Learning Req.	Pre-trained	Pre-trained	RL + pre-train	YOLOv8 + GPT-3.5	Required	None
Educational suitability	Low	High	Potential	High	Moderate	High

The proposed multimodal system achieves high accuracy (Voice = 96.2%, OCR = 95.8%) with a cycle time of 4.3 seconds, outperforming many complex, high-cost, or GPU-dependent methods in terms of cost, simplicity, and offline capability. Unlike YOLO-based or transformer-driven systems that require large datasets or GPU acceleration, the proposed system operates efficiently on low-cost Raspberry Pi hardware, requiring no pre-training. Its scalability and modularity further enhance its relevance in educational automation, offering a low-latency, fully offline alternative for real-time interaction tasks. The results validate that integrating voice, vision, and inverse kinematics on a low-cost embedded platform can achieve automation tasks typically requiring industrial-grade systems. The results affirm that this multimodal robotic approach is a practical and scalable solution for interactive human–robot collaboration.

Table 3 shows the method of collecting results for capturing success rate, which uses a simple method of determining the number of success test cases divided by the number of overall test cases (100 in our test trial setup). A trial is made up of 100 such test cases (each test case is a student listing). A test case is considered a failure if either one of voice or OCR or the robotic arm (precision) or a combination of either of the two produces a failure. The combination producing failures are termed ‘overlap’.

3.1. Critical analysis of system performance

While the proposed ROVAA system demonstrates strong performance across multiple metrics—voice recognition (96.2%), OCR + matching (95.8%), and inverse kinematics accuracy (97.6%), resulting in an overall system success rate of 92.8%—certain limitations and trade-offs must be acknowledged.

Error propagation across modules: The overall system accuracy (92.8%) is lower than individual module accuracies due to cascaded dependency. Errors in voice recognition or OCR directly impact downstream processes such as matching and robotic actuation. Sensitivity to environmental conditions: The voice recognition module may experience reduced accuracy in noisy classroom environments, while the OCR system is sensitive to lighting variations, handwriting quality, and camera positioning. Robotic Precision Constraints: Although the robotic arm achieves a pointing error of < 1 cm, minor deviations can accumulate due to servo backlash, calibration drift, and mechanical tolerances, especially over repeated operations. Processing Latency and Throughput: The average cycle time of ~4.3 seconds per entry is acceptable for small to medium classrooms but may become a bottleneck in large-scale deployments. Offline dependency constraints: The fully offline design ensures privacy and independence from network infrastructure. Dataset and Testing Scope: The evaluation was conducted on a finite and controlled dataset (500 samples), which may not fully capture real-world variability such as diverse accents and classroom conditions.

3.2. Limitations and future work

Although the proposed system demonstrates promising results for automated attendance marking, several limitations remain. The primary constraint arises from the 3-DOF robotic arm, whose limited workspace restricts interaction to a fixed set of calibrated screen points. This reduces flexibility when operating across different display sizes or layouts. Future designs incorporating additional degrees of freedom or adaptive kinematic planning could substantially improve reachability and operational robustness.

Environmental factors also affect performance. The OCR module is susceptible to variations in lighting, glare from reflective screens, and inconsistent font properties, occasionally leading to reduced text-recognition accuracy. Future enhancements may include controlled illumination, anti-glare filtering, or the integration of deep learning–based text detection models to improve reliability across diverse visual conditions. Adaptive noise and image processing - Incorporating noise filtering algorithms and adaptive image pre-processing can improve robustness in real-world environments

In terms of audio processing, the offline ASR system sometimes encounters difficulty with strong accents, background noise, and variability introduced by Bluetooth microphones. Developing accent-robust models, noise suppression pipelines, or lightweight on-device fine-tuning could enhance recognition process. Additional features such as automatic screen calibration, expanded command vocabularies, real-time performance analytics, cloud-linked attendance management could improve adaptability and user experience. Hybrid edge–cloud architecture could be engineered: While maintaining offline capability, optional integration with cloud services could enable model updates, improved OCR/voice accuracy. User-centric evaluation (*e.g.*, usability, acceptance, or workflow efficiency) and a more detailed statistical analysis is not performed and is being planned.

4. CONCLUSION

This work presents ROVAA, a low-cost AI-driven robotic attendance automation system that uniquely integrates offline speech recognition (Vosk), OCR-based text extraction (Tesseract), and a 3-DOF robotic arm controlled via inverse kinematics on a Raspberry Pi 4—an offline multimodal combination not previously demonstrated for classroom attendance automation. Unlike cloud-dependent or single-modality approaches, ROVAA operates entirely on embedded hardware, preserving data privacy while eliminating network dependency. The system achieves 96.2% speech recognition accuracy, 95.8% OCR accuracy, 97.6% robotic arm precision, and 92.8% overall success rate, confirming feasibility of reliable, offline classroom automation.

Beyond attendance marking, the modular architecture scales readily to related administrative tasks—laboratory sign-in, library access logging, and examination hall management, through reconfiguration of the voice vocabulary and screen calibration map alone, without hardware redesign. This makes ROVAA particularly suited to resource-constrained settings such as rural schools and institutions in low-connectivity regions where cloud-based solutions raise cost or data-sovereignty concerns. Its modular architecture further allows adaptation to related administrative tasks, including laboratory sign-in, library access logging, and examination hall management—by reconfiguring the voice command vocabulary and screen calibration map without changes to the underlying hardware or control framework. The system additionally serves as a hands-on educational platform for robotics, embedded systems, computer vision, and AI.

The broader impact of this work extends to institutional automation, assistive technologies, and administrative robotics, where similar frameworks can be adapted for tasks such as document handling, lab assistance, and interactive learning support. The emphasis on offline operation also addresses growing concerns related to data privacy, security, and dependency on cloud infrastructure, positioning ROVAA as a cost-effective and privacy-preserving model for intelligent automation in sensitive institutional contexts.

Despite its promising results, several opportunities for improvement remain. Deep learning-based OCR and advanced speech models to improve accuracy under challenging conditions, higher DOF robotic arms and integrating closed-loop feedback mechanisms, parallel processing for deployment in larger classroom settings, and hybrid edge–cloud architectures are some of the areas being currently worked.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
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Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, RKN. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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