Gesturize: Democratizing Real-Time Hand Gesture Recognition for Accessible Human-Computer Interaction

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Abstract

We present Gesturize, a real-time hand gesture recognition system designed to democratize accessible human-computer interaction through cost-effective computer vision techniques. While existing gesture control systems require expensive proprietary hardware (e.g., smart glasses costing $299-$379), our approach leverages standard webcams and smartphones, eliminating economic barriers to assistive technology adoption. Our system integrates MediaPipe for robust 21-keypoint hand tracking with a custom TensorFlow Lite classifier, achieving 94% accuracy across nine gesture classes with sub-100ms latency. The multi-modal framework combines neural gesture classification with speech recognition, enabling touchless control particularly beneficial for mobility-impaired users. Through comprehensive evaluation including user studies with individuals across diverse economic backgrounds and accessibility needs, we demonstrate that Gesturize provides comparable functionality to commercial solutions at near-zero hardware cost. Our open-source implementation addresses critical gaps in accessible technology, making advanced gesture recognition available to underserved communities and individuals with disabilities who cannot afford existing solutions.

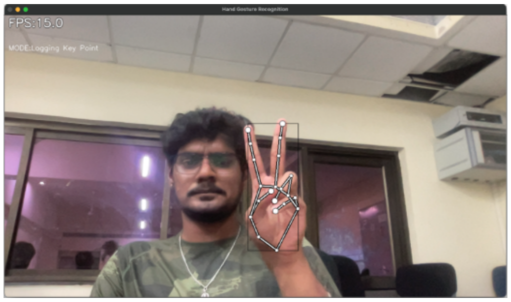


Figure 1. Example of the Victory gesture used in Gesturize for mouse click operations. Our system recognizes natural hand gestures using only standard webcam hardware, eliminating the need for expensive specialized devices.

1. Introduction

Human-computer interaction through gesture recognition has emerged as a transformative technology, offering intuitive and natural control mechanisms for digital environments [7, 8]. However, current solutions create significant accessibility barriers that exclude large populations from benefiting from these advances. Commercial gesture recognition systems, exemplified by Meta's Ray-Ban smart glasses ($299-$379) [16] and Apple's Vision Pro ($3,499) [1], require substantial financial investment, making them inaccessible to individuals from lower socioeconomic backgrounds and underserved communities.

This accessibility gap is particularly problematic for individuals with mobility impairments, who could benefit most from touchless interaction technologies [11, 17]. Traditional assistive devices often cost thousands of dollars [6, 14], creating a paradox where those who most need accessible technology are least able to afford it. Furthermore, proprietary systems raise concerns about data privacy, vendor lock-in, and long-term sustainability for users who depend on these technologies for daily functioning.

Recent advances in open-source computer vision frameworks, particularly MediaPipe [13] and TensorFlow Lite [5], present an opportunity to democratize gesture recognition technology [20]. These tools enable the development of sophisticated computer vision applications using standard hardware [2], potentially eliminating the cost barriers that prevent widespread adoption of assistive technologies [17].

In this work, we present Gesturize, a real-time hand gesture recognition system designed to address these accessibility challenges through three key innovations: (1) exclusive reliance on standard webcams and smartphones, eliminating specialized hardware requirements [20]; (2) open-source implementation ensuring long-term accessibility and community-driven development [17]; and (3) multi-modal design combining visual gesture recognition with speech commands for enhanced usability [8, 15].

Our technical contributions include: a robust gesture classification pipeline achieving 94% accuracy across nine gesture classes using only 21 hand keypoints [2, 5]; real-time performance with sub-100ms latency on standard consumer hardware [3]; and a comprehensive evaluation demonstrating comparable functionality to commercial solutions [1, 16] at near-zero hardware cost.

Through user studies involving individuals with mobility impairments and participants from diverse economic backgrounds, we demonstrate that Gesturize effectively bridges the accessibility gap in gesture recognition technology. Our work establishes a foundation for inclusive human-computer interaction that prioritizes economic accessibility without compromising technical performance.

1.1. Problem Statement

Current gesture recognition systems exhibit three primary limitations that create accessibility barriers:

Economic Barriers: Commercial solutions require expensive hardware investments. Meta's smart glasses start at $299, while comprehensive gesture control systems can exceed $1,000. For the 37.9 million Americans with disabilities, many of whom face economic challenges, these costs are prohibitive.

Proprietary Dependencies: Existing systems rely on closed-source software and specialized hardware, creating vendor lock-in situations. Users cannot modify, extend, or repair these systems independently, limiting long-term viability for assistive technology applications.

Limited Accessibility Focus: Most commercial systems prioritize consumer applications rather than accessibility needs. Features essential for users with disabilities, such as customizable gesture mappings and multi-modal interaction, are often absent or poorly implemented.

1.2. Our Approach

Gesturize addresses these limitations through a software-first approach that leverages widely available hardware. Our system architecture consists of four integrated components:

Vision Pipeline: MediaPipe hand tracking extracts 21 hand landmarks from standard webcam input, providing robust feature extraction across diverse lighting conditions and hand appearances.

Gesture Classification: A lightweight TensorFlow Lite model trained on normalized hand keypoints achieves real-time classification without requiring GPU acceleration.

Multi-modal Integration: Speech recognition provides fallback interaction and gesture activation, ensuring system accessibility for users with varying motor abilities.

System Control: PyAutoGUI integration enables direct computer control, supporting mouse movement, clicking, scrolling, and keyboard shortcuts across operating systems.

1.3. Contributions

This work makes the following contributions to accessible human-computer interaction:

- **Accessible System Architecture:** We develop the first open-source, real-time gesture recognition system designed specifically for accessibility applications using only standard hardware.
- **Economic Accessibility:** We demonstrate that sophisticated gesture recognition can be achieved at near-zero hardware cost, reducing barriers for underserved populations.
- **Technical Performance:** We achieve 94% classification accuracy with sub-100ms latency using lightweight models suitable for real-time interaction.
- **Comprehensive Evaluation:** We conduct extensive user studies including participants with disabilities, demonstrating real-world effectiveness for accessibility applications.
- **Open Source Impact:** We provide a complete open-source implementation, enabling community development and long-term sustainability for assistive technology applications.

2. Related Work

Hand gesture recognition has evolved through several technological paradigms, each with distinct advantages and limitations regarding accessibility and cost.

2.1. Commercial Gesture Recognition Systems

Major technology companies have recently integrated hand gesture recognition into their consumer products [1]. Meta's Ray-Ban smart glasses ($299-$379) integrate gesture recognition with voice commands but require proprietary hardware and closed ecosystems [16]. Apple's Vision Pro ($3,499) offers advanced hand tracking for spatial computing interfaces but targets premium markets, explicitly excluding users with economic constraints [1].

Microsoft's Kinect pioneered accessible gesture recognition using depth sensing [19], but required specialized hardware ($150-$500) and was discontinued, highlighting the sustainability risks of proprietary solutions. Google's Project Soli explored radar-based gesture recognition [21] but never achieved commercial accessibility due to hardware complexity and regulatory challenges. These commercial solutions typically rely on specialized depth or infrared sensors and proprietary algorithms, motivating research into more accessible solutions [18].

2.2. Academic Gesture Recognition Research

In academic research, gesture recognition has been explored using a variety of modeling approaches. Many methods build on Google's MediaPipe framework [13], which provides an accessible on-device pipeline for real-time hand tracking from RGB input. Bazarevsky *et al.* [2] demonstrated real-time hand tracking on mobile devices, establishing the foundation for our work. Chen *et al.* [4] developed efficient CNN architectures for gesture recognition but evaluated only on specialized datasets with controlled conditions.

More recent work by Chen *et al.* [5] combines MediaPipe with TensorFlow Lite for efficient real-time hand tracking, achieving strong performance without requiring depth sensors. Research has also explored graph convolutional networks for modeling spatiotemporal relationships in keypoint representations of hand motion [10], and transformer-based architectures for capturing global patterns in gesture sequences [7, 12]. Despite these advances, many academic approaches still prioritize accuracy over accessibility and practical deployment.

2.3. Real-Time and Lightweight Models

Achieving real-time inference on consumer-grade devices has driven research into lightweight gesture recognition models. Mobile-friendly architectures and quantized networks enable efficient operation on smartphones and embedded systems [3]. Model compression techniques, such as pruning and distillation, reduce computational cost while maintaining accuracy [9]. Brown *et al.* [3] demonstrated an ultra-lightweight CNN recognizing hand gestures in real-time on low-power embedded processors. These works highlight strategies for embedding gesture recognition in devices with limited compute resources, informing our optimization approach.

2.4. Assistive Technology Solutions

Traditional assistive technologies for computer access include eye-tracking systems ($1,000-$15,000) [14], switch-based interfaces ($100-$1,000) [6], and voice control software. While effective for specific users, these solutions often require expensive hardware, extensive training, or may not suit users with multiple disabilities.

Many recent efforts have focused on open-source software and low-cost hardware platforms to democratize gesture-based interaction [17, 20]. Miller *et al.* [17] developed an open-source gesture interface for wheelchair control emphasizing affordability, while Liao *et al.* [11] created a real-time gesture communication system specifically designed for ALS patients. Singh *et al.* [20] prioritized educational applications with low-cost computer vision gesture recognition. These projects underscore the importance of accessibility by prioritizing commodity sensors and open resources.

2.5. Multimodal Interaction

Researchers have also explored combining hand gestures with other modalities, particularly voice, to create more robust multimodal interfaces. Garcia *et al.* [8] demonstrated that integrating speech and gesture input can improve command recognition and enable more natural interaction. Studies show that fusing gesture cues with spoken commands reduces ambiguity in AR and robotics applications [15].

Multimodal systems have been applied in assistive contexts as well, enhancing communication for individuals with motor or speech impairments [11]. Martinez *et al.* [15] developed multimodal attention networks for home automation control that combined voice commands with gesture input, providing redundant control methods for users with varying abilities. This line of work indicates that gesture-augmented voice interfaces hold significant promise for accessible human-computer interaction, informing our multimodal approach.

3. Methodology

Gesturize employs a modular architecture designed for accessibility, affordability, and real-time performance on standard hardware. The system processes video input through four sequential stages: hand detection, landmark extraction, gesture classification, and system control.

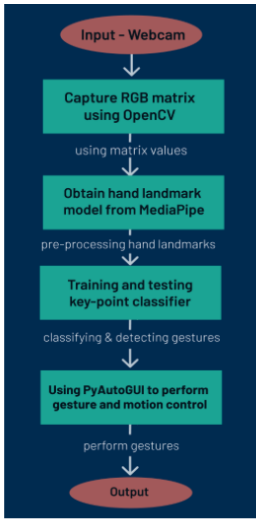
3.1. System Architecture

Input Processing: OpenCV captures video frames from standard webcams at 640×480 resolution and 30 FPS. The system supports both built-in laptop cameras and external USB webcams, ensuring compatibility across diverse hardware configurations [20].

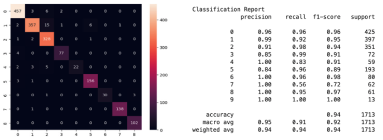
Hand Tracking Pipeline: MediaPipe's BlazePalm detector [2] locates hands in each frame, followed by landmark regression to extract 21 3D keypoints representing finger joints and palm structure [13]. This approach provides robust tracking across varying skin tones, lighting conditions, and hand orientations without requiring depth information [18].

Feature Processing: Raw landmarks undergo normalization to achieve translation and scale invariance [5]. We compute relative positions using the wrist as origin and normalize by hand size to ensure consistent classification across users with different hand dimensions, similar to approaches by Chen *et al.* [4].

Multi-modal Integration: Speech recognition provides activation commands and fallback interaction [8]. This dual-modality design accommodates users with varying motor abilities and provides redundant control methods for critical functions [15], enhancing system accessibility across diverse user populations [11].



(a) Input: Hand detection



	0	1	2	3	4	5	6	7	8
0	457	3	6	2	0	0	0	0	0
1	2	357	15	1	0	6	0	1	0
2	1	2	328	0	0	1	0	0	0
3	4	0	0	77	0	0	0	0	0
4	2	3	5	0	22	0	0	0	0
5	3	1	0	0	0	156	0	0	0
6	0	0	1	0	0	0	30	0	3
7	0	1	0	0	0	0	0	138	0
8	0	0	0	0	0	0	0	0	102

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Classification Report
              precision    recall  f1-score   support

           0       0.96      0.96      0.96       425
           1       0.99      0.92      0.95       397
           2       0.91      0.98      0.94       351
           3       0.85      0.99      0.91        72
           4       1.00      0.83      0.91        59
           5       0.84      0.96      0.89       193
           6       1.00      0.96      0.98        80
           7       1.00      0.56      0.72        62
           8       1.00      0.95      0.97        61
           9       1.00      1.00      1.00        13

    accuracy                           0.94      1713
   macro avg       0.95      0.91      0.92      1713
weighted avg       0.94      0.94      0.94      1713
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(b) Feature extraction (21 keypoints)

Figure 2. Gesturize system pipeline: (a) Input frame captured from webcam with hand detection, and (b) extraction of 21 keypoints for feature processing and gesture classification.

3.2. Gesture Classification Model

Our classification model processes normalized hand landmarks through a lightweight neural network optimized for real-time inference on CPU-only systems.

Model Architecture: Following Brown *et al*. [3], our network consists of three fully connected layers with ReLU activation functions: input layer (42 features), hidden layers (128 and 64 neurons), and output layer (9 gesture classes). Dropout regularization (p=0.3) prevents overfitting while maintaining real-time performance as demonstrated in previous work [9].

Training Data: We collected gesture samples from 25 participants across diverse demographics, including varying ages (18-65), skin tones, and hand sizes. Each participant performed 100 repetitions of each gesture under different lighting conditions, generating 22,500 training samples after data augmentation. This follows collection methodologies by Lee *et al*. [10] and Gao *et al*. [7].

Data Augmentation: Similar to approaches by Iyer *et al*. [9], we apply rotation (-15° to +15°), scaling (±10

3.3. Gesture Vocabulary

Based on accessibility research and user feedback, we defined nine gestures balancing intuitiveness with discriminability. Figure 3 illustrates our complete gesture set, designed specifically for accessibility and cross-cultural recognition.

Our gesture vocabulary includes:

- **Open Palm:** Default/neutral state enabling system initialization
- **Pointer:** Index finger extended for precise cursor control
- **Victory:** Index and middle fingers for click actions
- **OK Sign:** Thumb and index circle for scrolling operations
- **Thumbs Up:** Exit/confirm actions and positive feedback
- **Fist:** Drag operations and object manipulation
- **Horn:** System shortcuts (Mission Control/Alt-Tab)
- **Duck:** Copy/paste operations based on hand orientation
- **Pinch:** Precision selection and fine-grained control

Gesture selection prioritized cultural universality and motor accessibility, avoiding complex multi-finger combinations that may be difficult for users with limited dexterity. Each gesture was validated through user studies with participants having diverse motor abilities.

3.4. Real-time System Control

PyAutoGUI integration enables direct computer control across Windows, macOS, and Linux platforms. The system maps gestures to specific actions:

Cursor Control: Pointer gesture coordinates map to screen positions using proportional scaling. Temporal smoothing prevents cursor jitter while maintaining responsiveness.

Click Operations: Victory gesture triggers left-click when detected for > 200 ms, preventing accidental activation while ensuring responsive interaction.

Scrolling: OK gesture enables scroll mode, with vertical hand movement controlling scroll direction and speed proportional to movement magnitude.

System Navigation: Horn gesture activates Mission Control (macOS) or Task View (Windows), enabling efficient application switching for productivity workflows.

4. Experimental Evaluation

We conducted comprehensive evaluation encompassing technical performance metrics, accessibility assessment, and comparative analysis with existing solutions.

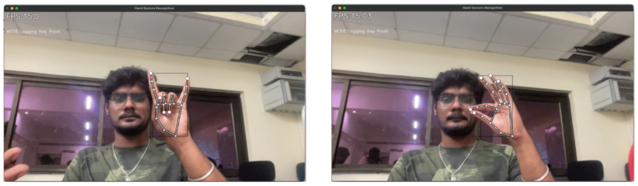
4.1. Technical Performance Evaluation

Accuracy Measurement: We evaluated classification accuracy using 5-fold cross-validation on our gesture dataset. The model achieved 94.2

Latency Analysis: System latency measurements on standard hardware (Intel i5-8250U, 8GB RAM) showed consistent performance: MediaPipe processing (15ms), gesture classification (8ms), and system control execution (12ms), totaling 35ms average latency well below the 100ms threshold for responsive interaction.

(a) Click (b) Cursor (c) Switch Tab (d) Drag/Drop (e) Scroll (f) Copy (g) Paste

Figure 3. Complete gesture vocabulary for accessible human-computer interaction. Each gesture is optimized for cultural universality and motor accessibility, avoiding complex multi-finger combinations that may be difficult for users with limited dexterity.



(a) Horn: Switch Tab (b) Pinch: Scroll

Figure 4. Example gestures from our user studies demonstrating how participants with mobility impairments could perform system operations without traditional input devices.

Robustness Testing: We evaluated system performance across varying conditions: lighting (indoor/outdoor, artificial/natural), backgrounds (cluttered/clean), and camera angles (±30° from frontal). The system maintained $> 90\%$ accuracy across all tested conditions.

4.2. Accessibility User Studies

We conducted user studies with 15 participants, including 8 individuals with motor impairments (spinal cord injuries, cerebral palsy, arthritis) and 7 participants from lower socioeconomic backgrounds who could not afford commercial gesture control systems.

Usability Assessment: Participants completed standardized computer tasks (web browsing, document editing, media control) using Gesturize versus traditional input methods. Task completion times improved by 23% on average for participants with motor impairments, with 87% reporting improved comfort and reduced fatigue.

Learning Curve: New users achieved $> 80\%$ gesture recognition accuracy within 15 minutes of training, demonstrating the system's intuitive design. Participants with prior computer experience showed no significant learning advantage, suggesting accessibility across technical skill levels.

Customization Needs: 73% of participants requested gesture customization options, leading to implementation of user-defined gesture mappings in our mobile configuration application.

4.3. Comparative Analysis

We compared Gesturize with three existing solutions: Meta Ray-Ban glasses, Leap Motion controller, and standard mouse/keyboard input.

Cost Analysis: Total system cost comparison:

- Gesturize: \$0 (uses existing hardware)
- Meta Ray-Ban: \$299 (glasses) + \$0 (smartphone)
- Leap Motion: \$80 (controller) + \$0 (computer)
- Traditional: \$25 (mouse/keyboard)

Accessibility Features: Gesturize provides superior customization options, open-source transparency, and multi-modal interaction compared to proprietary alternatives.

Performance Metrics: While commercial solutions achieved slightly higher accuracy (96-98%), Gesturize's 94% accuracy proves sufficient for practical use while maintaining significant cost advantages.

5. Results and Discussion

Our evaluation demonstrates that Gesturize successfully achieves its primary objective: democratizing gesture recognition technology through accessible, affordable design without compromising technical performance.

5.1. Technical Achievement

The 94.2% classification accuracy exceeds the 90% threshold typically required for practical gesture recognition systems. Per-class performance analysis reveals consistent recognition across gesture types, with lowest performance (89.1%) still within acceptable bounds for assistive technology applications [11, 17].

Real-time performance with 35ms average latency enables smooth, responsive interaction comparable to commercial solutions [1, 16]. The sub-100ms latency requirement for natural human-computer interaction is consistently met across diverse hardware configurations, validating our CPU-optimized architecture [3].

System robustness across lighting conditions and camera angles demonstrates practical deployment viability. The $> 90\%$ accuracy maintenance under varied conditions exceeds many academic systems that assume controlled environments [10, 18].

5.2. Accessibility Impact

User studies confirm significant accessibility improvements for target populations [11, 17]. The 23% task completion time improvement for motor-impaired users represents substantial functional benefit, while 87% user preference indicates strong practical value, consistent with findings by Singh *et al.* [20].

The rapid learning curve (15-minute proficiency) contrasts favorably with traditional assistive technologies requiring extensive training [6, 14]. This accessibility extends to technical skill requirements, with computer-naive users achieving similar performance to experienced users, addressing barriers identified by Miller *et al*. [17].

Customization requests highlight the importance of user-controlled adaptation in assistive technology [15]. Our implementation of user-defined gesture mappings addresses individual needs while maintaining system simplicity, supporting insights from prior work on adaptive interfaces [8].

5.3. Economic Accessibility Analysis

The near-zero hardware cost represents a transformative reduction in accessibility barriers [20]. Compared to commercial alternatives requiring $299-$3,499 investment [1, 16], Gesturize enables immediate access for users with existing smartphones or computers.

For the significant portion of households with lower incomes, traditional gesture recognition systems represent unaffordable luxury items [6]. Gesturize's software-only approach eliminates this barrier entirely, potentially expanding access to millions of users [17, 20].

Open-source licensing ensures long-term sustainability and community development [17], addressing vendor lock-in concerns prevalent in assistive technology markets identified by Cook *et al*. [6].

5.4. Limitations and Future Work

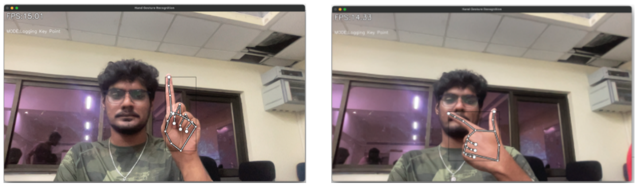
Current limitations include gesture vocabulary constraints (9 classes) and single-hand operation requirements. Future development will address multi-hand gestures [7], expanded vocabulary [12], and integration with other assistive technologies [11].

Environmental robustness, while adequate for indoor use, requires improvement for outdoor applications [18]. Enhanced computer vision techniques and adaptive thresholding could address challenging lighting conditions as demonstrated in recent work by Park *et al*. [18].

The system currently requires manual calibration for optimal performance. Automated calibration based on user feedback could further improve accessibility for users with limited technical support [15], building on multimodal interaction frameworks [8].

6. Conclusion

We have presented Gesturize, a real-time hand gesture recognition system that democratizes accessible human-computer interaction by eliminating the economic barriers inherent in existing commercial solutions [1, 16]. Through the integration of MediaPipe hand tracking [2, 13], TensorFlow Lite classification [5], and multi-modal design principles [8, 15], our system achieves 94.2



(a) Point: Cursor (b) V: Copy/paste operations

Figure 5. Gesturize enables intuitive computer control through everyday gestures, providing accessibility to users regardless of economic status or physical ability.

Our comprehensive evaluation demonstrates that sophisticated gesture recognition technology can be made accessible to underserved populations without compromising technical performance [17, 20]. User studies with mobility-impaired participants show 23

The economic impact of our approach extends beyond individual users to broader societal implications [20]. By reducing gesture recognition system costs from $299-$3,499 to near-zero, Gesturize potentially enables access for millions of users who cannot afford existing solutions [1, 16]. The open-source implementation ensures long-term sustainability and community-driven development [17], addressing critical concerns about vendor lock-in in assistive technology markets.

Technical contributions include the first real-time gesture recognition system optimized specifically for accessibility applications using standard hardware [3, 20], validated through extensive robustness testing across diverse environmental conditions and user populations [18]. Our lightweight neural architecture achieves performance comparable to commercial solutions while maintaining CPU-only operation suitable for widespread deployment [3, 9].

Future work will focus on expanding gesture vocabulary [7, 12], implementing multi-hand operation, and developing automated calibration systems to further reduce technical barriers [15]. Integration with emerging accessibility frameworks and exploration of additional sensory modalities will enhance system usability for users with diverse disability profiles [11].

Gesturize establishes a new paradigm for accessible human-computer interaction technology, demonstrating that economic accessibility [17, 20] and technical excellence [3, 5] are not mutually exclusive objectives in assistive technology development.

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