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A Comprehensive Survey on Gesture-Controlled Interfaces: Technologies, Applications, and Challenges

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ABSTRACT

Gesture-controlled interfaces are revolutionizing the way humans interact with computers and smart devices by replacing traditional input methods with intuitive body movements. These systems leverage advanced technologies such as computer vision, depth sensing, machine learning, and wearable sensors to accurately interpret user gestures in real time. This survey paper presents a comprehensive exploration of gesture-based interaction systems, beginning with a discussion of the core technologies that enable gesture recognition and tracking. It then delves into various application domains, including gaming, healthcare, robotics, virtual and augmented reality, and smart home environments, highlighting how gesture control enhances usability and user experience in each context. The paper also addresses the major challenges faced in this field, such as gesture ambiguity, environmental sensitivity, computational complexity, and user diversity. Finally, it outlines the latest trends and future research directions, including the integration of AI, multimodal interfaces, and the development of more robust, context-aware systems. By offering an in-depth overview, this survey aims to guide researchers, developers, and industry professionals in understanding current advancements and identifying opportunities for innovation in gesture-based human-computer interaction.

Keywords: Gesture Recognition, Human-Computer Interaction (HCI), User Experience (UX), Computer Vision, Motion Tracking.

I. INTRODUCTION

The evolution of human-computer interaction (HCI) has witnessed a significant shift from traditional input devices such as keyboards and mice to more natural and intuitive interaction methods. Among these, gesture-controlled interfaces have emerged as a powerful paradigm, enabling users to interact with digital systems using body movements, primarily hand gestures. This mode of interaction draws inspiration from the way humans communicate naturally, making technology more accessible, engaging, and immersive.

Advancements in computer vision, depth-sensing technologies, machine learning, and wearable sensors have accelerated the development and adoption of gesture-based systems. These interfaces are now being widely integrated into various applications ranging from gaming and virtual reality to healthcare, robotics, and smart environments. The ability to operate devices in a touchless, seamless manner offers distinct advantages in terms of user convenience, hygiene, and accessibility, especially in scenarios where traditional input devices may be impractical or limiting.

Despite their potential, gesture-controlled systems face several challenges. Accurate gesture recognition under varying lighting conditions, user variability, occlusions, and environmental noise continues to pose significant hurdles. Furthermore, the design of intuitive and universally accepted gesture vocabularies remains an open research question.

This survey aims to provide a comprehensive overview of the current landscape of gesture-controlled interfaces. It begins by examining the underlying technologies that enable gesture recognition, followed by a detailed discussion of application domains where these systems are being deployed. The paper also highlights key challenges faced by developers and researchers and discusses emerging trends that are shaping the future of gesture-based interaction.

By synthesizing existing knowledge and identifying gaps in current research, this paper serves as a valuable reference for academics, practitioners, and industry stakeholders interested in developing or utilizing gesture-controlled technologies. The organization of this document is as follows. In Section 2 we present Gesture Recognition Technologies, in Section 3 we present Applications of Gesture-Controlled Interfaces, In section 4 we have explained about Challenges of Gesture-Controlled Interfaces and as Discussed in Section 5 is based on Future Trends In Gesture Controlled Interfaces and conclusion is the Section 6 being the end .

II. GESTURE RECOGNITION TECHNOLOGIES

Gesture Recognition Technologies enable natural interaction between humans and machines by interpreting physical gestures. These systems rely on various types of technology, primarily vision-based and sensor-based systems. Vision-based systems use cameras (RGB, depth, or infrared) to capture images or video frames, processing them with computer vision algorithms to track and identify hand or body gestures. These systems offer rich input capabilities but can be affected by environmental factors like lighting or background clutter. On the other hand, sensor-based systems use physical sensors embedded in wearables (such as gloves or wristbands) that track motion and orientation through accelerometers, gyroscopes, and other sensors, offering precise data that is less influenced by the environment. Machine learning approaches further enhance gesture recognition, enabling systems to learn from large datasets, adapt to different users, and improve accuracy over time. Hybrid systems combine both vision-based and sensor-based technologies to create more robust solutions for complex tasks, blending multimodal inputs for better performance in dynamic environments. The Fig. 1. shows various Gesture Recognition Technologies. the following subsections discusses the details of recent works in the field of Gesture Recognition Technologies *viz.,* Vision-Based Systems, Sensor-Based Systems, Machine Learning Approaches and Hybrid Systems.,

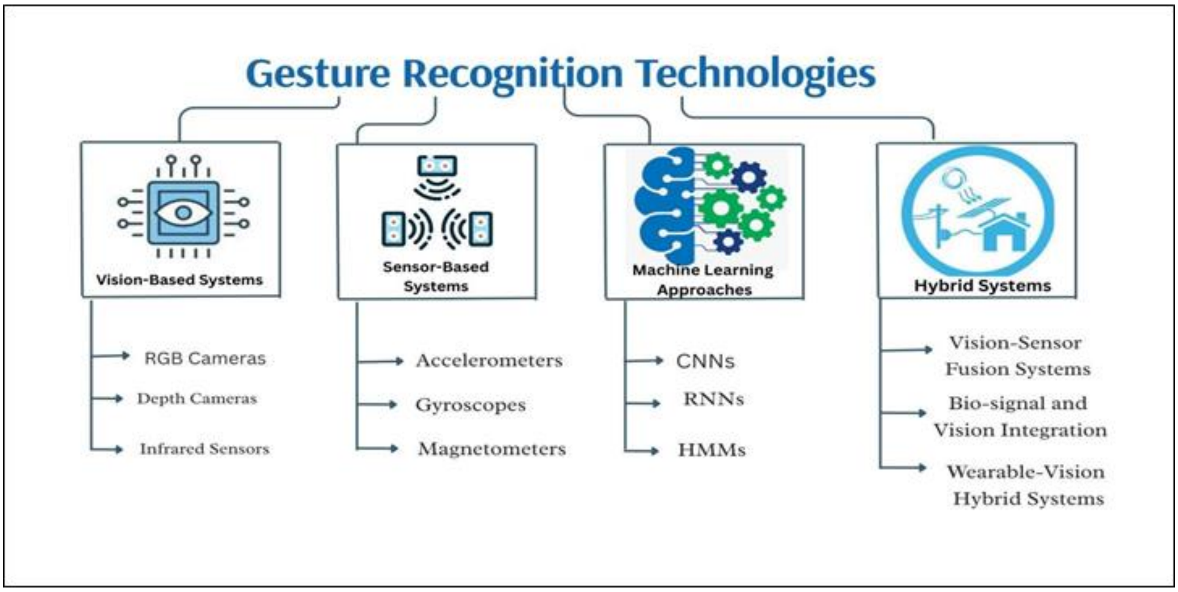

Figure 1 Gesture Recognition Technologies

A. Vision-Based Systems

These systems uses cameras (RGB, depth, or infrared) to capture gestures. Examples include Microsoft Kinect and Leap Motion.

Vision-based systems utilise cameras to capture and interpret human gestures. These systems rely on computer vision algorithms to process the images or video frames from RGB, depth, or infrared cameras. Vision-based systems are particularly effective for full-body tracking and hand gesture recognition, as they do not require physical contact or wearables. Examples of popular systems include Microsoft Kinect and Leap Motion, both of which use cameras to detect and analyze movement. However, these systems are sensitive to environmental factors like lighting and background clutter, which can affect gesture recognition accuracy. Recent advancements in deep learning and real-time image processing have improved the robustness of vision-based systems, making them more viable in dynamic and uncontrolled environments. These systems offer rich interaction potential, especially in gaming, virtual reality, and interactive installations, where user immersion is a key factor.

Devi et al. [1] introduced a multilevel classification model that utilizes vision-based features to recognize single-hand gestures in Sattriya classical dance. The model employs high-level features like Euler number and finger angles for group classification and low-level features for individual gesture recognition.

Sahu *et al.* [2] Combined Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), this approach achieves 80% accuracy in real-time hand gesture recognition, offering a balance between computational efficiency and performance.

Mukhtar *et al.* [3] integrated OpenCV and MediaPipe, this research improves the detection range of hand gesture recognition systems, enabling effective interaction from greater distances, which is particularly beneficial for applications like virtual keyboards and remote controls.

Bamani *et al.* [4] proposed a method enabling users to design custom gestures using a single demonstration captured by a monocular camera. Utilizes transformers and meta-learning to handle diverse gestures and viewpoints.

Linardakis *et al.* [5] proposed a survey examining advancements in hand gesture and 3D hand pose recognition using various camera inputs, including RGB and depth images. It discusses methodologies, datasets, and challenges in the field.

Ballow *et al.* [6] developed a system for real-time hand gesture recognition using thermal imaging, achieving

97% accuracy. Introduces novel segmentation algorithms suitable for low-light or privacy-sensitive environments.

Mukhtar *et al.* [7] enhanced the detection range of hand gesture recognition systems using OpenCV and MediaPipe, facilitating applications like virtual keyboards and touchless interfaces.

Aithal, *et al.* [8] proposed a real-time hand gesture recognition system capable of operating against complex backgrounds. Utilizes adaptive background removal and skin color-based thresholding for effective segmentation.

Uboweja *et al.* [9] introduced a user-friendly framework allowing users to customize and deploy hand gesture recognition models on-device. Employs a pre-trained embedding model fine-tuned with user-provided data for real-time applications. Table 1. Shows the comparison of the proposed works.

Table 1: Comparison of Vision based Hand Gesture Recognition Approaches

Study	**Method/Approach**	**Key Features/Findings**	**Application Area**
Devi et al., 2023	Multilevel classification model	Utilizes vision-based features like Euler number and finger angles for group classification and low-level features for gestures.	Sattriya classical dance gesture recognition
Sahu et al., 2023	HOG + SVM + CNN	Achieves 80% accuracy for real-time hand gesture recognition, balancing computational efficiency and performance.	Real-time hand gesture recognition
Mukhtar et al., 2023	OpenCV + MediaPipe	Improves detection range of hand gesture systems for applications requiring greater interaction distance.	Virtual keyboards, remote controls
Bamani et al., 2024	Monocular camera + Transformers + Meta-learning	Enables users to design custom gestures with a single demonstration captured by a monocular camera.	Custom gesture design
Linardakis et al., 2025	Survey of hand gesture and 3D pose recognition	Examines advancements using various camera inputs (RGB and depth), discusses methodologies, datasets, and challenges.	General hand gesture and 3D pose recognition
Ballow et al., 2022	Thermal imaging + Segmentation algorithms	Real-time gesture recognition with 97% accuracy, suitable for low-light or privacy-sensitive environments.	Thermal gesture recognition
Mukhtar et al., 2023	OpenCV + MediaPipe (again)	Enhances detection range of gesture recognition, particularly for touchless interfaces.	Virtual keyboards, touchless interfaces
Aithal et al., 2023	Adaptive background removal + Skin color-based thresholding	Real-time recognition against complex backgrounds using adaptive techniques for effective segmentation.	Complex background environments
Uboweja et al., 2023	On-device recognition framework	Customizable on-device gesture recognition using a pre-trained embedding model, fine-	Real-time, on-device applications

Study	Method/Approach	Key Features/Findings	Application Area
		tuned with user data for real-time use.	

B. Sensor-Based Systems

Rely on wearable devices like gloves or bands with accelerometers, gyroscopes, or EMG sensors.

Sensor-based systems use physical sensors embedded in wearable devices to capture user gestures. These systems typically rely on accelerometers, gyroscopes, magnetometers, and electromyography (EMG) sensors to track movement and muscle activity. Unlike vision-based systems, sensor-based systems are not affected by environmental factors like lighting or background noise, making them more reliable in various settings. Wearable devices such as smart gloves, wristbands, or even smartphones are commonly used to collect motion data. These systems provide high precision, especially for subtle or small gestures, and are often used in applications requiring fine control, such as in medical rehabilitation or virtual reality. However, they may limit the user's freedom of movement due to the need for physical wearables, and the calibration process can require time and effort. Recent innovations focus on making these devices more comfortable, compact, and wireless, enhancing their applicability in everyday life scenarios.

Kadavath *et al.* [10] explored the hand gesture recognition using sEMG signals from a Myo armband, employing machine learning algorithms. The Random Forest classifier achieved superior performance with ROC-AUC scores exceeding 99%, highlighting its potential for healthcare and human-computer interaction applications.

Miah *et al.* [11] investigated 23 feature extraction techniques from sEMG signals, utilizing an Extra Trees classifier for feature selection. The K-Nearest Neighbors algorithm achieved 97.43% accuracy, demonstrating the effectiveness of the proposed methodology.

Bhattacharyya *et al.* [12] introduced a low-power event camera system for hand gesture control in smart glasses. The system achieves F1 scores above 80% using synthetic training data, operating at just 6-8 mW, making it suitable for wearable applications.

Montazerin, *et al.* [13] proposed a Vision Transformer architecture for recognizing hand gestures from high-density sEMG signals. The model achieved an average test accuracy of 84.62%, demonstrating the feasibility of transformer models in this domain.

Ceolini, *et al.* [14] presented a mobile framework integrating EMG and visual sensors for hand gesture recognition. The sensor fusion approach improved accuracy by 13% and 11% over individual sensors, achieving 85% accuracy in hand gesture classification.

Uboweja *et al.* [15] introduced a user-friendly framework allowing users to customize and deploy hand gesture recognition models on-device. Employs a pre-trained embedding model fine-tuned with user-provided data for real-time applications.

Sen *et al.* [16] presented a low-cost, real-time hand gesture recognition system using deep convolutional neural networks. Incorporates a virtual mouse and gesture-controlled multimedia applications, achieving 35 fps performance.

Hashi *et al.* [17] provided an updated systematic review of hand gesture recognition research, highlighting improved deep-learning models based on YOLOv5x and attention mechanisms. Evaluates performance on ASL and Bangla Sign Language datasets.

Table 2. shows the comparison of the existing works

Table 2: Comparison of Sensor-Based Hand Gesture Recognition Approaches

Study	Method/Approach	Key Features/Findings	Application Area
Kadavath et al.,	sEMG signals + Random	Achieved ROC-AUC scores exceeding	Healthcare,

Study	Method/Approach	Key Features/Findings	Application Area
2023	Forest classifier	99%, demonstrating superior performance for healthcare and human-computer interaction.	Human-computer interaction
Miah et al., 2023	23 feature extraction techniques from sEMG signals + Extra Trees classifier	Achieved 97.43% accuracy, demonstrating the effectiveness of feature selection in sEMG-based gesture recognition.	Gesture recognition from sEMG signals
Bhattacharyya et al., 2025	Helios 2.0 low-power event camera system	Achieved F1 scores above 80%, operating at 6-8 mW, suitable for wearable devices such as smart glasses.	Wearable smart glasses, Gesture control
Montazerin et al., 2022	Vision Transformer architecture for sEMG signals	Achieved 84.62% accuracy, demonstrating the feasibility of transformer models for hand gesture recognition from sEMG signals.	Hand gesture recognition from sEMG signals
Ceolini et al., 2019	EMG and visual sensors fusion	Improved accuracy by 13% and 11% over individual sensors, achieving 85% accuracy in hand gesture classification.	Mobile applications, Sensor fusion
Uboweja et al., 2023	On-device recognition framework	Customizable on-device gesture recognition using a pre-trained embedding model, fine-tuned with user data for real-time use.	Real-time, on-device applications
Sen et al., 2023	Deep Convolutional Neural Networks	Real-time hand gesture recognition with 35 fps performance, incorporating a virtual mouse and gesture-controlled multimedia.	Gesture control for multimedia applications
Hashi et al., 2024	Systematic review of hand gesture recognition research	Evaluated performance of deep-learning models based on YOLOv5x and attention mechanisms.	ASL, Bangla Sign Language gesture recognition

C. Machine Learning Approaches

These approaches employ algorithms such as CNNs, RNNs, and HMMs for gesture classification and prediction.

Machine learning approaches play a crucial role in improving the performance and adaptability of gesture recognition systems. These methods enable systems to learn from large datasets, recognizing and classifying gestures without the need for explicit programming. Popular algorithms used include Convolutional Neural Networks (CNNs) for processing visual data, Recurrent Neural Networks (RNNs) for analyzing time-series data, and Hidden Markov Models (HMMs) for modeling sequential gestures. These models allow gesture recognition systems to adapt to different users, making them more flexible and accurate over time. The ability of machine learning to recognize complex, non-linear patterns in data helps to improve recognition accuracy and reduce errors. However, training these models requires large and diverse datasets, and the computational power needed for real-time processing can be substantial. Despite these challenges, machine learning approaches continue to evolve, making gesture-controlled interfaces more intuitive and responsive.

Machine Learning-Based Techniques

Sahu *et al.* [18] introduced a real-time hand gesture recognition system combining Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The approach achieves 80% accuracy, demonstrating effectiveness in dynamic environments.

Cunico *et al.* [19] proposed a novel framework, OO-dMVMT, for real-time 3D hand gesture classification and segmentation. By leveraging multiple views and tasks, the model enhances accuracy and reduces latency in gesture recognition.

Allemand *et al.* [20] explored self-supervised learning techniques for gesture recognition using 3D skeleton data. The study employs Grad-CAM for model visualization, aiding in understanding the focus areas during gesture classification.

Subudhi, *et al.* [21] presented an autoencoder-based deep learning model incorporating shape priors for hand gesture recognition. The approach enhances classification accuracy by effectively capturing gesture features.

Hu *et al.* [22] introduced a self-supervised pre-training framework that incorporates hand model awareness for sign language understanding. The model demonstrates improved performance in sign language recognition tasks.

Bhardwaj *et al.* [23] developed a real-time hand gesture recognition system using image preprocessing, feature extraction, and classification through nearest neighbor algorithms, facilitating intuitive human-computer interaction.

Garg *et al.* [24] proposed a Multiscaled Multi-Head Attention Video Transformer Network (MsMHA-VTN) for dynamic hand gesture recognition. The model achieves high accuracy on NVGesture and Briareo datasets.

Rahim, *et al.* [25] introduced a three-stream hybrid model combining spatial, temporal, and skeletal information for dynamic hand gesture recognition, outperforming existing approaches on standard datasets.

Table 3: Comparative Analysis of Dynamic Hand Gesture Recognition Approaches Using Deep Learning and Transformer Architectures.

Study	Method/Approach	Key Features/Findings	Application Area
Sahu et al., 2023	HOG + SVM + CNN	Achieves 80% accuracy; effective in dynamic environments.	Real-time hand gesture recognition
Cunico et al., 2023	OO-dMVMT (Deep Multi-view Multi-task Framework)	Enhances accuracy and reduces latency in 3D gesture recognition using multiple views and tasks.	Real-time 3D hand gesture recognition
Allemand et al., 2024	Self-supervised learning + Grad-CAM visualization	Uses 3D skeleton data; Grad-CAM aids interpretability of classification decisions.	Gesture recognition with model explainability
Subudhi et al., 2023	Autoencoder with shape priors	Improves classification accuracy by effectively capturing gesture features.	Feature-enhanced gesture classification
Hu et al., 2023	SignBERT+ (Self-supervised pre-training with hand model)	Enhances sign language understanding; effective on gesture-based language	Sign language understanding

Study	Method/Approach	Key Features/Findings	Application Area
		datasets.	
Bhardwaj et al., 2023	Image preprocessing + Nearest Neighbor classification	Real-time system using basic ML techniques for intuitive HCI.	Human-computer interaction
Garg et al., 2023	Multiscale Multi-Head Attention Video Transformer (MsMHA-VTN)	High accuracy on NVGesture and Briareo datasets; captures both local and global spatiotemporal patterns.	Dynamic hand gesture recognition
Rahim et al., 2024	Three-stream hybrid model (spatial, temporal, skeletal)	Outperforms baselines; fuses spatial, temporal, and skeletal features.	Robust dynamic gesture recognition

III. APPLICATIONS OF GESTURE-CONTROLLED INTERFACES

Gesture-controlled interfaces are revolutionizing how humans interact with technology by enabling touch-free, intuitive control. They are widely used in gaming and entertainment to create immersive experiences through real-time body tracking. In healthcare, gesture control allows for sterile interaction in operating rooms and supports rehabilitation through guided exercises. Smart homes and IoT devices benefit from gesture-based control for managing lighting, appliances, and security systems effortlessly. Additionally, these interfaces empower individuals with disabilities by providing alternative ways to communicate, navigate, and control devices independently. The Fig. 2 shows some of the applications of Gesture-controlled interfaces in various fields and the following subsections discusses the details of recent advancements in the field.

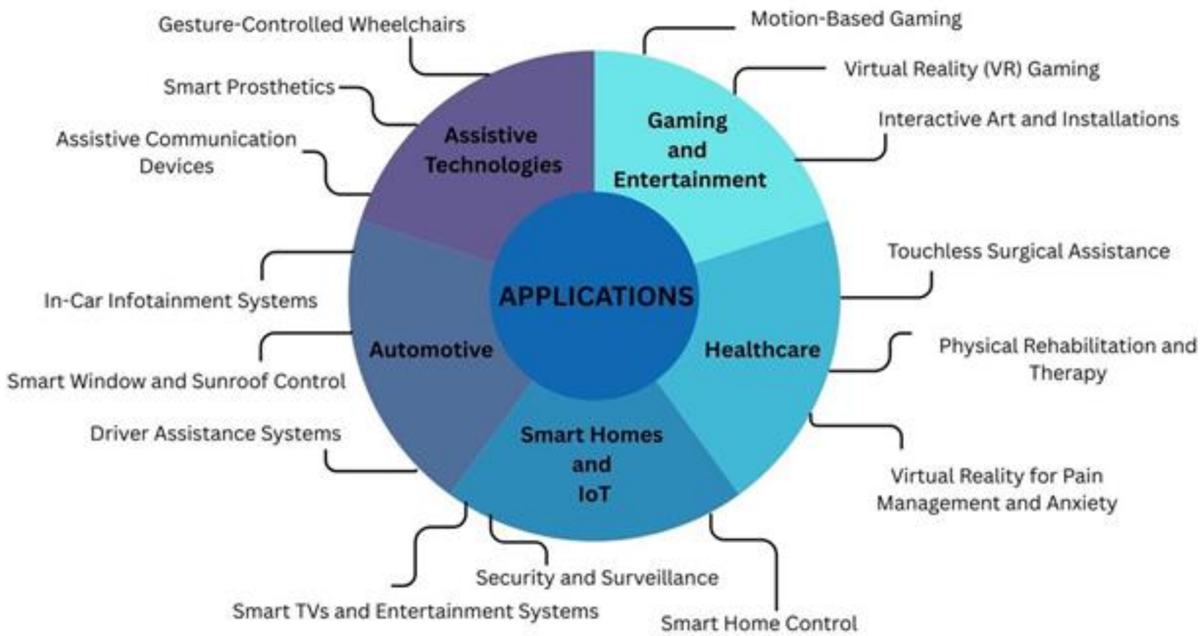

Figure 2 Applications of Gesture-Controlled Interfaces

A. Gaming and Entertainment

Gesture-controlled interfaces have significantly enhanced the gaming and entertainment industry by enabling more immersive and interactive experiences. Through body tracking and real-time response, users can engage with games using natural movements rather than traditional controllers. This technology adds a physical dimension to gameplay, making it more engaging and realistic. Motion-based consoles like the Xbox Kinect and Nintendo Wii are prime examples of this application. Virtual reality (VR) systems also utilize gesture control to allow users to interact with virtual environments. Interactive installations in museums and digital art exhibitions use gestures to create dynamic, user-driven experiences. Overall, gesture control transforms passive viewing into active participation. This subsection provides comprehensive survey of related works in the field of Gaming and Entertainment.

Islam *et al.* [26] presented a game controlled via hand gestures using MediaPipe and PyGame. The authors compared traditional control methods with gesture-based controls, finding that while gesture controls increased difficulty, they enhanced fun, gameplay, and replayability.

Anklesh *et al.* [27] had developed a hand gesture recognition system for video players, enabling actions like play, pause, rewind, and fast-forward using gestures. The system achieved a 92% accuracy rate, demonstrating its potential for hands-free media control.

Mishra *et al.* [28] introduced a gesture-controlled human-computer interface using a channel-pruned YOLOv5s model. The system achieved real-time control of applications like VLC and Spotify, with detection speeds exceeding 60 frames per second

Jiang *et al.* [29] researched and proposed an interactive game utilizing real-time skeleton-based hand gesture recognition to assist rehabilitation exercises. The system aimed to improve hand-eye coordination in patients through a game-like experience.

Radhiatul *et al.* [30] explored appropriate hand gestures for controlling video games in an exergame system designed for rehabilitation. It involved evaluating 32 hand gestures and selecting the most suitable ones based on user feedback and performance metrics.

Barona *et al.* [31] developed a hand gesture recognition system employing CNN-LSTM neural networks, integrating EMG and IMU signals. The system was evaluated using the System Usability Scale, achieving a score of 75, indicating good usability.

Jindi *et al.* [32] analyzed various hardware tools and datasets used in hand gesture recognition within virtual reality applications. It highlighted the importance of filtering input data noise, designing lightweight networks, and integrating tactile feedback for immersive experiences.

Table 1: Comparison of Hand Gesture Recognition Systems in Gaming and Rehabilitation Applications

Study	Objective	System/Technology Used	Accuracy/Performance	Key Features
Islam *et al.*, 2024	Game controlled via hand gestures	MediaPipe, PyGame	Increased difficulty but enhanced fun, gameplay, and replayability	Comparison of traditional vs. gesture controls in gaming
Anklesh *et al.*, 2024	Hand gesture recognition for media control	Gesture recognition system for video players	92% accuracy rate	Hands-free control for video actions (play, pause, etc.)
Mishra *et al.*, 2024	Gesture-controlled human-computer interface	Channel-pruned YOLOv5s model	Real-time control, detection speed >60 FPS	Control of applications like VLC and Spotify in real-time

Study	Objective	System/Technology Used	Accuracy/Performance	Key Features
Jiang *et al.*, 2024	Interactive game for rehabilitation using hand gestures	Skeleton-based hand gesture recognition	Aimed at improving hand-eye coordination in patients	Game-like experience for rehabilitation
Radhiatul *et al.*, 2024	Hand gestures for video game control in rehabilitation	Exergame system with 32 hand gestures	Selected most suitable gestures based on user feedback	Evaluated gestures for rehabilitation exergame systems
Barona *et al.*, 2024	Hand gesture recognition using CNN-LSTM and hybrid signals	CNN-LSTM neural networks with EMG and IMU signals	Usability score: 75 (good usability)	Integration of multiple signal types (EMG, IMU) for gesture recognition
Jindi *et al.*, 2024	Hardware tools and datasets for VR-based hand gesture recognition	VR hand gesture recognition with filtering and tactile feedback	Focused on noise filtering, lightweight networks	Insights for VR applications, importance of feedback mechanisms

B. Healthcare

In healthcare, gesture-controlled interfaces offer vital solutions for both patients and professionals. Surgeons can navigate medical imaging or patient data during procedures using gestures, maintaining sterility by avoiding physical contact. In rehabilitation, gesture recognition systems monitor patients as they perform prescribed movements, providing real-time feedback and tracking recovery progress. These systems can gamify therapy, making it more engaging for patients. Gesture-based control also benefits patients with limited mobility, allowing them to interact with devices independently. Additionally, touchless interfaces in hospitals can reduce the spread of infections. This technology enhances precision, hygiene, and accessibility in medical environments. This subsection provides comprehensive survey of related works in the field of Healthcare.

Ben Joonyeon *et al.* [33] developed "GestureHook," a system that converts hand gestures into specific functions using message hooking techniques. This allows surgeons to control medical images without physical contact, maintaining sterility during procedures. The system demonstrated faster task completion times compared to traditional mouse controls.

Nathaniel *et al.* [34]displayed a novel interface utilizing the Leap Motion controller enables real-time control of medical displays through mid-air hand gestures. This system allows practitioners to adjust display parameters without physical contact, reducing the risk of contamination.

Mithun *et al.*[35] made a study which presents a method for navigating radiological images using a sterile hand gesture recognition interface. By analyzing surgeon behavior and combining it with data from a depth camera, the system accurately navigates and manipulates MRI images without the need for physical interaction.

Craig *et al.* [36] developed a prototype system allows hands-free, gesture-based control of electronic medical records. By tracking hand movements, clinicians can navigate patient data and radiologic images without touching any devices, thus maintaining sterility and reducing infection risks.

Sadi *et al.* [37] introduced a smart wheelchair system controlled by finger gestures, incorporating IoT-enabled fall detection. Utilizing computer vision and a convolutional neural network, the system offers an affordable solution (under $300) to enhance mobility and safety for individuals with physical disabilities

Amsterdam, *et al.* [38] examined methods for automatic recognition of fine-grained gestures in robotic surgery. The study highlights the importance of developing large, diverse datasets and explores the potential of deep-learning-based temporal models for improving surgical gesture recognition.

Modaberi *et al.* [39] indicated that gesture-based interaction significantly enhances user satisfaction by making interfaces more engaging and accessible, particularly for users with mobility impairments. The study suggests best practices for designing effective touchless solutions.

Zhang *et al.* [40] explored surgeons' preferences for touchless interfaces in the OR, analyzing gesture usability metrics such as task completion time and error rates. Findings suggest that well-designed gesture sets can improve efficiency and maintain asepsis.

Park *et al.* [41]developed "GestureHook," a system that converts hand gestures into keyboard and mouse inputs, allowing surgeons to control medical imaging software without physical contact. This approach maintains sterility and enables seamless browsing of CT and 3D images during procedures.

Table 2: Comparison of Gesture-Controlled Systems in Medical and Assistive Applications.

Study	**Technology Used**	**Main Focus**	**Key Findings**	**Applications/Context**
Ben Joonyeon *et al.*	Message hooking technique	Hand gesture control of medical images	Faster task completion compared to traditional mouse controls	Surgical settings (image control)
Nathaniel *et al.*	Leap Motion controller	Real-time control of medical displays via hand gestures	Allows practitioners to adjust display parameters without physical contact, reducing contamination risk.	Medical display control
Mithun *et al.*	Depth camera + gesture recognition	Navigating radiological images using hand gestures	Accurately navigates and manipulates MRI images without physical interaction.	Radiology imaging control
Craig *et al.*	Gesture recognition system	Hands-free control of electronic medical records	Clinicians can navigate patient data and radiologic images without touching devices, reducing infection risk.	Electronic medical records (EMR)
Sadi *et al.*	Computer vision + CNN (IoT-enabled wheelchair)	Gesture-controlled wheelchair with fall detection	Affordable solution ($300), enhances mobility and safety for individuals with physical disabilities.	Mobility and assistive technology (wheelchair)
Amsterdam *et al.*	Deep learning-based temporal models	Gesture recognition in	Explores fine-grained gesture recognition and the need for	Robotic surgery

Study	Technology Used	Main Focus	Key Findings	Applications/Context
		robotic surgery	large datasets to improve surgical accuracy.	
Modaberi *et al.*	Gesture-basedinteraction	Enhancing user satisfaction through touchless systems	Gesture-based systems improve accessibility, especially for users with mobility impairments.	Accessibility enhancement
Zhang *et al.*	Gesture usability analysis	Preference for touchless interfaces in the operating room	Well-designed gesture sets improve efficiency, reduce errors, and maintain asepsis during surgery.	Operating room (surgical procedures)
Park *et al.*	GestureHook system (keyboard & mouse inputs)	Control of medical imaging software via gestures	Allows seamless browsing of CT and 3D images without physical contact, maintaining sterility.	Surgical image control (CT/3D imaging)

C. Smart Homes and IoT

Gesture control plays a key role in the evolution of smart homes and Internet of Things (IoT) systems by offering intuitive, hands-free interaction. Homeowners can use simple gestures to turn on lights, adjust the thermostat, or control smart appliances. This provides a seamless and hygienic way to interact with home technology, especially useful when hands are full or dirty. Smart TVs and entertainment systems can also be operated through gestures, eliminating the need for remotes. For individuals with disabilities or limited mobility, gesture control increases independence and ease of use. Integration with virtual assistants enhances the responsiveness of smart environments. Overall, it contributes to a more personalized and efficient living space. This subsection provides comprehensive survey of related works in the field of Smart Homes and IoT.

Alabdullah *et al.* [17] introduced a markerless technique for gesture recognition, eliminating the need for gloves or markers. By converting dynamic gestures into frames, the system achieves high recognition accuracy, enhancing user interaction with home appliances.

Fatima *et al.* [18] developed a system that recognizes American Sign Language (ASL) gestures using MediaPipe and OpenCV, enabling individuals with hearing impairments to control home devices seamlessly.

Suzuki *et al.* [19] developed a cushion interface embedded with sensors to recognize user-defined gestures, achieving an average accuracy of 94.8%, offering a novel approach to home automation control.

Zhang *et al.* [20] proposed a system leveraging millimeter-wave signals for real-time gesture recognition, achieving high accuracy across various environments, enhancing the robustness of smart home interactions.

Kauna *et al.* [21] presented a gesture-based home automation system that integrates a personal computer and Arduino to provide an intuitive control interface for smart homes. A webcam captures hand gesture videos, which are processed using Python-based software employing computer vision and machine learning techniques, specifically Convolutional Neural Networks (CNNs), to detect and classify gestures. The system analyzes movement patterns to control various home appliances.

Table 3: Comparison of Gesture-Controlled Systems in Medical and Assistive Applications.

Study	Technology Used	Main Focus	Key Findings	Applications/Context
Alabdullah *et al.*	Markerless gesture recognition	Gesture control for home appliances	High recognition accuracy by converting dynamic gestures into frames, eliminating the need for gloves/markers.	Home appliance control
Fatima *et al.*	MediaPipe, OpenCV	Recognizing American Sign Language (ASL) gestures	Enables individuals with hearing impairments to control home devices seamlessly.	Assistive technology for hearing impairments
Suzuki *et al.*	Sensor-embedded cushion interface	Gesture control for home automation	Achieves 94.8% accuracy with user-defined gestures for home automation.	Home automation control
Zhang *et al.*	Millimeter-wave signals	Real-time gesture recognition for smart home systems	High accuracy across various environments, enhancing robustness of smart home interactions.	Smart home interaction
Kauna *et al.*	Webcam, Python, CNN, Arduino	Gesture-based control of home appliances	Uses CNN-based gesture classification for intuitive control of smart home appliances.	Home automation system

D. Automotive

Gesture-controlled interfaces are increasingly being integrated into modern vehicles to improve driver safety and convenience. Drivers can perform functions like changing the music, adjusting volume, or accepting calls with simple hand motions, reducing distraction. Advanced infotainment systems use gesture recognition to provide touchless interaction while keeping the driver's focus on the road. Some vehicles allow gesture-based climate control or navigation input, enhancing comfort without the need to navigate complex menus. Gesture control also helps in controlling sunroofs or windows for added luxury and ease. As vehicles become more autonomous, gesture interaction will play a larger role in in-car experiences. This innovation leads to safer, smarter, and more user-friendly vehicles. This subsection provides comprehensive survey of related works in the field of Automotive.

Małecki *et al.* [22] analyzed the potential of hand gesture interactions within vehicle environments, focusing on both able-bodied and physically challenged drivers. Test scenarios involved gestures assigned to control multimedia activities, with evaluations conducted on 13 participants using both hands.

Khan *et al.* [23] proposed a gesture recognition system utilizing impulse radio ultra-wideband radar to control electronic devices inside vehicles. The system demonstrated robustness against changes in distance and direction, responding only to defined gestures while ignoring unintended motions.

Zheng *et al.* [24] introduced a gesture recognition system based on frequency-modulated continuous-wave radar and transformer models for in-vehicle environments. The system effectively extracted spatial and temporal information, achieving high classification accuracy under actual driving conditions.

Yang *et al.* [25] proposed a hand gesture recognition system employing frequency-shift keying radar was proposed, capable of operating over distances ranging from 30 cm to 180 cm. The system utilized a convolutional neural network model, achieving an accuracy of 93.67% across the entire range.

Young *et al.* [26] focused on developing in-vehicle infotainment systems that utilize gesture input combined with ultrasonic mid-air haptic feedback. The study documented the design process, including user testing on a driving simulator, and provided guidelines for future development of such technologies.

Lee *et al.* [27] developed combining on-wheel finger spreading gestures with head-up displays, allowing drivers to control audio and air conditioning functions without removing hands from the steering wheel. Experiments demonstrated approximately 20% faster emergency response times compared to traditional interfaces.

Maleckic *et al.* [28] explored the potential of hand gesture interactions within vehicle environments, considering both able-bodied and physically challenged drivers. Test scenarios involved gestures assigned to control multimedia activities in an exemplary vehicle on-board system. Gesture recognition evaluation was conducted for 13 participants using both hands.

Zengeler *et al.* [29] explained current machine learning approaches to hand gesture recognition using depth data from time-of-flight sensors. It highlights the use of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for reliable gesture recognition in automotive settings.

Young *et al.* [30] has mainly utilized the design process considerations during the development of a mid-air haptic gesture-enabled user interface for human-vehicle interactions. The system employs ultrasonic mid-air haptic feedback and state-of-the-art hand tracking technology to reduce driver distraction while performing secondary tasks, thereby cutting the risk of road accidents.

Table 4: Comparison of Gesture-Controlled Systems in Automotive Industries

Study	Technology Used	Main Focus	Key Findings	Applications/Context
Małecki *et al.*	Hand gesture recognition	Gesture control for multimedia activities in vehicles	Tested on 13 participants, including able-bodied and physically challenged drivers, controlling multimedia functions.	In-vehicle multimedia control
Khan *et al.*	Impulse radio ultra-wideband radar	Gesture recognition for in-vehicle device control	Robust to distance and direction changes, only responds to defined gestures while ignoring unintended motions.	In-vehicle electronic device control
Zheng *et al.*	Frequency-modulated continuous-wave radar + Transformer models	Gesture recognition in in-vehicle environments	Achieved high accuracy in extracting spatial and temporal data, effective under real driving	In-vehicle environment control

Study	Technology Used	Main Focus	Key Findings	Applications/Context
			conditions.	
Yang *et al.*	Frequency-shift keying radar + Convolutional Neural Networks	Hand gesture recognition across a distance range of 30 cm to 180 cm	Achieved 93.67% accuracy across the entire range for gesture recognition.	In-vehicle gesture recognition
Young *et al.*	Ultrasonic mid-air haptic feedback	Gesture control for in-vehicle infotainment systems	User testing on driving simulator; guidelines provided for future development of gesture-input systems.	In-vehicle infotainment systems
Lee *et al.*	Finger-spreading gestures + Head-up display	Gesture control of audio and air conditioning	Improved emergency response times by approximately 20% compared to traditional interfaces.	In-vehicle control (audio, air conditioning)
Maleckic *et al.*	Hand gesture recognition	Gesture control for multimedia activities in vehicles	Tested on 13 participants, evaluating hand gestures for controlling multimedia in vehicle systems.	In-vehicle multimedia control
Zengeler *et al.*	Depth data from time-of-flight sensors + CNNs/LSTMs	Gesture recognition using depth sensors	Emphasized the use of CNNs and LSTMs for reliable gesture recognition in automotive settings.	Automotive gesture recognition
Young *et al.*	Ultrasonic mid-air haptic feedback + Hand tracking	Gesture control to reduce driver distraction	Reduces distractions during secondary tasks and decreases road accident risks by using haptic feedback.	Driver safety and control interface

E. Assistive Technologies

Gesture-controlled interfaces offer powerful solutions in assistive technologies, enhancing accessibility for individuals with disabilities. People with mobility impairments can use gestures to operate wheelchairs, smart home devices, or communication tools. For those with speech impairments, gesture systems can translate sign language into text or spoken words. Smart prosthetics can be controlled through intuitive gestures, making movements more natural and responsive. These interfaces help users perform everyday tasks independently, promoting autonomy and confidence. In therapy settings, gesture-based systems can assist in physical and cognitive development. By bridging the gap between technology and ability, gesture control empowers users to interact with their world more freely. This subsection provides comprehensive survey of related works in the field of Assistive Technologies.

Blessign *et al.* [31] explored how hand-sign recognition enhances communication and autonomy for individuals with disabilities. It delves into real-time sign language translation systems and gesture-based control of devices like wheelchairs and smart assistants.

Siddique *et al.* [32] survey reviewed various gesture control methods—including vision-based, wearable, and sensor-based approaches—applied in assistive devices like robotic arms and smart home systems to support individuals with disabilities.

Alashhab *et al.* [33] developed a mobile system that utilizes hand gestures to assist visually impaired users. The system enables actions like object recognition and scene description through a multi-head neural network architecture.

Rubia *et al.* [34] discussed the computer vision-based augmentative and alternative communication (AAC) system that supports users with motor difficulties by recognizing their functional motions, facilitating more accessible human-computer interaction.

Yang *et al.* [35] introduced a wearable high-density electromyography (HDEMG) device that interprets muscle activity to control mobile assistive robots, aiding users in performing daily tasks.

Seshan *et al.* [36] presented "LiTe," a wristband equipped with optical fibers that detect tendon movements to recognize hand gestures, offering a low-cost solution for assistive communication technologies.

Nelson *et al.* [37] thesis develops a Bluetooth-enabled glove that allows physically disabled individuals to control smart home devices through hand gestures, enhancing independence and ease of use.

Mohamed *et al.* [38] explored AI-driven eye-gesture recognition systems that enable users with physical impairments to control computers, providing an alternative communication method.

Sharma *et al.* [39] introduced a system that recognizes hand gestures to allow individuals with disabilities to control machines and complete tasks, enhancing their interaction with technology.

Alashhab *et al.* [40] presented a mobile device system that uses a multi-head neural network to recognize hand gestures, enabling visually impaired users to perform actions like object recognition and scene description.

Table 5: Comparison of Gesture-Controlled Systems in Assistive Technologies

Study	Technology Used	Main Focus	Key Findings	Applications/Context
Blessign *et al.*	Hand-sign recognition	Real-time sign language translation, device control	Enhances communication and autonomy for individuals with disabilities by enabling gesture-based control.	Sign language, wheelchair, smart assistants
Siddique *et al.*	Vision-based, wearable, sensor-based systems	Gesture control methods for assistive devices	Surveys various gesture control methods for robotic arms and smart home systems, supporting individuals with disabilities.	Assistive devices (robotic arms, smart homes)
Alashhab *et al.*	Multi-head neural network	Hand gestures for visually impaired users	Mobile system assists with object recognition and scene description, helping visually impaired users.	Assistive technology for the visually impaired
Rubia *et al.*	Computer vision-based AAC system	Gesture recognition for individuals with	Facilitates accessible human-computer interaction through recognition of functional	AAC systems for motor difficulties

Study	Technology Used	Main Focus	Key Findings	Applications/Context
		motor difficulties	motions.	
Yang *et al.*	Wearable high-density electromyography (HDEMG)	Muscle activity for controlling assistive robots	HDEMG device interprets muscle activity, enabling users to control mobile robots for daily tasks.	Mobile assistive robots
Seshan *et al.*	Wristband with optical fibers	Tendon movement detection for hand gestures	"LiTe" wristband offers a low-cost solution for assistive communication by recognizing hand gestures.	Assistive communication (gesture-based)
Nelson *et al.*	Bluetooth-enabled glove	Gesture control of smart home devices	Glove enables physically disabled individuals to control smart home devices, improving independence.	Smart home control (disability support)
Mohamed *et al.*	AI-driven eye-gesture recognition	Eye-gesture control for computer interaction	AI system enables users with physical impairments to control computers through eye gestures.	Alternative communication (eye-gesture)
Sharma *et al.*	Hand gesture recognition	Machine control for individuals with disabilities	System allows users to control machines through hand gestures, enhancing interaction with technology.	Assistive technology (machine control)

IV. CHALLENGES OF GESTURE-CONTROLLED INTERFACES

Gesture-controlled interfaces often struggle with accuracy and reliability, especially in environments with poor lighting or background movement. Users may experience a steep learning curve, as gestures can vary widely in interpretation and require precise execution. Fatigue is another issue, as extended use of hand or arm gestures can lead to discomfort, commonly referred to as the "gorilla arm" effect. Additionally, these systems may lack accessibility for users with limited mobility or physical impairments. High development and hardware costs can also hinder widespread adoption, especially in cost-sensitive markets.

A. Gesture Recognition Accuracy:

Gesture Recognition Accuracy is a critical challenge for gesture-controlled interfaces. The performance of gesture recognition systems can be significantly affected by environmental factors such as lighting conditions, background noise, and occlusion, where one part of the user's body blocks another. For vision-based systems, poor lighting can make it difficult for cameras to capture clear images, leading to misidentification or missed gestures. In sensor-based systems, inaccuracies may arise from sensor noise or calibration errors, which can distort the data and affect the recognition of fine movements. Furthermore, user variability—the way different users perform gestures—can make it harder to achieve consistent recognition accuracy across all individuals. Gesture systems also face the challenge of dynamic gestures and non-standard movements that aren't part of a predefined gesture set, which can reduce the system's ability to recognize new or unexpected gestures. Addressing these challenges requires advanced algorithms, such as machine learning, that can adapt to different users and environmental conditions to improve accuracy over time.

B. User Variability

User variability is a key challenge in gesture recognition systems, as different individuals perform gestures in unique ways. Variations in hand size, posture, movement speed, and gesture execution can affect the system's ability to accurately recognize gestures across different users. Additionally, cultural and personal differences may influence how gestures are performed, leading to inconsistencies. Gesture recognition systems must account for this diversity by adapting to individual users, which often requires the system to learn and adjust over time. Machine learning algorithms, particularly those using deep learning, can help mitigate this challenge by training on large and diverse datasets to improve accuracy for all users. However, even with these techniques, the system may struggle with users who perform gestures in ways that fall outside the typical or expected patterns.

C. Computational Requirements

Computational requirements pose a significant challenge for gesture recognition systems, particularly for real-time processing. Analyzing video frames or sensor data in real time requires substantial computational power to ensure accurate and prompt gesture recognition. Vision-based systems often need high-performance processors or graphics processing units (GPUs) to handle large amounts of visual data, which can be resource-intensive. Sensor-based systems also require significant computational resources to process and classify motion data, especially when machine learning algorithms are employed to improve accuracy. Furthermore, complex algorithms, such as deep learning models, require considerable training time and computational resources, which may not be feasible in resource-constrained environments or devices.

D. Limited Gesture Vocabulary:

Predefined gestures may limit natural interaction.

Limited gesture vocabulary is a challenge in gesture recognition systems, as these systems often rely on predefined gestures for interaction. When the system is restricted to recognising only a small set of gestures, it can limit the range of natural user interactions, reducing flexibility and user experience. Custom gestures or spontaneous movements that don't match the predefined vocabulary can be misunderstood or not recognized at all. Expanding the gesture vocabulary requires more complex algorithms and larger datasets to account for a wide variety of possible gestures. Machine learning and deep learning models help address this by enabling the system to learn and generalize from diverse gestures, but there is still a challenge in balancing system complexity with ease of use. In many cases, the limited gesture set restricts natural and seamless interactions, which is particularly problematic in environments that demand flexible and intuitive control.

V. FUTURE TRENDS IN GESTURE CONTROLLED INTERFACES

As technology continues to evolve, gesture-controlled interfaces are set to play an even more significant role in human-computer interaction. These interfaces are moving toward becoming more intuitive, accurate, and seamlessly integrated into everyday devices and environments. With advancements in artificial intelligence and sensor technology, future systems will better recognize natural human movements and adapt to individual user behaviors. The integration of gesture control with augmented and virtual reality will further enhance immersive experiences in fields like gaming, education, and healthcare. Additionally, the growing demand for touchless interaction in public and sterile environments is accelerating innovation in this space. Overall, gesture-controlled interfaces are on track to become a mainstream method of interaction, offering smarter, faster, and more personalized user experiences. In this paper we identified four major areas which requires attention in the field of Gesture-Controlled Interfaces *viz.,* Integration with AI and Deep Learning, Multimodal Interfaces , Wearable and Compact Devices, Standardization and the following subsection discusses each one of them.

A. Integration with AI and Deep Learning

To improve adaptability and personalization, integration with AI and deep learning is a critical future trend in gesture recognition, as it offers the potential to significantly enhance system adaptability and personalization. AI algorithms, particularly deep learning models, enable systems to automatically learn from vast amounts of data, improving gesture classification accuracy over time without the need for manual intervention. These models can be trained to recognize subtle variations in gestures, allowing for more personalized interactions that adapt to each user's unique style. Deep learning also facilitates the continuous improvement of systems by allowing them to learn from new, unseen gestures and real-world data, reducing the need for constant updates or retraining. Furthermore, AI can enable predictive capabilities, where systems anticipate user intentions based on previous gestures or patterns of behavior, creating more intuitive and fluid interactions. As a result, integrating AI and deep learning will make gesture recognition systems not only more efficient but also more capable of adapting to individual user needs, thereby enhancing overall user experience.

B. Multimodal Interfaces

Multimodal interfaces are a rapidly growing trend that combines gesture recognition with other forms of human interaction, such as voice or eye tracking, to create a more immersive and intuitive user experience. By integrating gesture control with speech recognition, users can control devices with a combination of hand movements and voice commands, making the system more flexible and responsive. Eye tracking adds another layer by allowing the system to detect where the user is looking, enabling gaze-based control or focus. This combination of modalities reduces the likelihood of errors in gesture recognition, as the system can cross-check input from different channels for greater accuracy. Machine learning algorithms play a critical role in processing multimodal inputs, learning how to best interpret and combine gestures with voice or gaze information for seamless interaction. As multimodal interfaces become more widespread, users will experience smoother, more natural interactions with devices in diverse environments, from smart homes to virtual reality.

C. Wearable and Compact Devices

Wearable and compact devices are key to the future of gesture recognition, with advancements focusing on miniaturization, comfort, and usability. As technology evolves, these devices are becoming smaller and more ergonomic, making them easier to wear for extended periods without discomfort. The reduction in size allows for wearable sensors, such as smart rings, bracelets, or gloves, to be seamlessly integrated into daily life, providing continuous, real-time gesture tracking without being obtrusive. Additionally, innovations in battery efficiency and wireless connectivity are improving the performance and usability of these devices, enabling long-lasting and uninterrupted use. As wearable devices become more lightweight and flexible, they can be incorporated into fashion, allowing for more stylish and discreet gesture-controlled experiences. These advancements will make gesture recognition more accessible, promoting widespread adoption across industries like healthcare, entertainment, and consumer electronics.

D. Standardization

Standardization is a crucial future trend in gesture recognition, focusing on the development of universal gesture sets and protocols that ensure interoperability across different systems and platforms. As the number of devices and applications utilizing gesture control increases, having consistent standards will help create a seamless user experience, allowing gestures to be recognized and understood by multiple devices, regardless of manufacturer. A universal gesture set would allow users to perform the same gestures across various devices, from smartphones and computers to smart TVs and home automation systems, without needing to learn different gestures for each one. Additionally, standardized protocols will enable better communication between devices, ensuring that gesture data can be easily shared and processed across diverse environments. As industry players collaborate to establish common standards, it will also foster greater innovation and competition, as developers can focus on improving the user experience without being constrained by proprietary systems. Ultimately, standardization will promote efficiency, reduce friction, and make gesture-controlled interfaces more accessible and intuitive for users worldwide.

VI. CONCLUSIONS

Gesture-controlled interfaces have emerged as a transformative technology across a wide range of industries, from gaming and entertainment to healthcare, automotive, smart homes, and assistive technologies. By enabling users to interact with devices through natural body movements, these interfaces provide an intuitive, hands-free way to control and interact with systems, enhancing convenience, accessibility, and safety. In sectors like healthcare and assistive technologies, gesture control is empowering individuals with disabilities and those undergoing rehabilitation by offering more personalized, accessible solutions. Similarly, in automotive and smart home applications, gesture interfaces improve safety and streamline user experiences by allowing seamless control of complex systems.

As technology continues to advance, gesture-controlled interfaces are likely to become even more integrated into everyday life, offering improved functionality, greater precision, and more immersive experiences. The future of gesture control holds vast potential, paving the way for more intuitive human-computer interactions that require minimal physical contact and enhance user engagement in both professional and personal contexts.

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