

IoT-Enabled Gesture Recognition for Smart Device Interaction

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Abstract- The Internet of Things (IoT) technology allows individuals to have new interfaces to communicate with devices that are smart. We present a Smart IoT Interface with Hand Gesture Recognition and Machine Learning in this work to enhance human-machine interaction (HMI) in smart environments. Being a wearable hand gesture recognition and control device, it relies on sensor networks and embedded systems to obtain real-time hand gesture feedback, which is later interpreted by advanced machine learning algorithms to allow natural and natural interaction with IoT devices. The suggested interface takes advantage of wireless communication and edge processing that allows the practical and low-latency processing of real-time data and cloud integration to provide additional device control and gain analytics. Its applications include IoT automation, home automation and an intelligent IoT control to a flexible and reliable system that enables the user to interact with devices connected to it. Findings suggest that the sugg

Keywords— Internet of Things (IoT), IoT Interface, Smart Devices, Wireless Communication, Sensor Networks, Edge Computing, Embedded Systems, IoT Automation, IoT Connectivity, Real-Time Data Processing, IoT Applications, Cloud Integration, IoT Control Systems, Smart Home Technology, Human-Machine Interaction (HMI), Wireless Communication, Automation and Control.

I. INTRODUCTION

The interface between human and machines has transformed with the modern technology evolving at a very rapid rate [1]. The use of traditional human-machine interface (HMI) e.g., keyboard, mouse and touchscreen has been proven to be functional but has recently been wanting in an era where HMI by nonintrusion, intuitiveness, and naturalness is a necessary tool [2]. The end product was, however, with the advancement of technology to have a device that would be able to identify human actions and movements beyond those of feelings or gestures such that a manipulator like a mechanical input device is not necessary anymore [3] [4]. Gesture recognition has been one of the most promising solutions in order to achieve this vision. It allows natural communication between machines and humans without the use of hands or body language [5]. The History and Future of Gestures Since time immemorial gestures have been among the most natural forms of information regarding language or culture: this is why they present such an exciting new way/interface/interaction with digital information [6]. The invention of the gesture-based interaction did not only make the user interfaces simpler to operate, but it also gave breakthrough potential to the aspect of accessibility whereby individuals with some degree of disability or those who have some restriction on the movements of their bodies would have

new opportunities to interact as they work with with a great deal of ease through the common service technology just of the help of the movement of hands [7] [8].

Gesture recognition has greater opportunities in combination with the Internet of Things (IoT) [9]. IoT is the linking of physical systems, sensors and devices through the Internet to facilitate them interact and transmit/ receive information and automatically complete some smart tasks Ibid [10]. The combination of motion recognition and IoT makes the environment effective to the extent that the gesture of a person can directly induce a change into the things [11]. This convergence gives depth to the totality of intelligent living whereby home, office and city respond in an intelligent way to human actions [12]. A case in point is that one can switch on lights, operate fans, control thermostats and manage home appliances without using buttons or smart phones, but through predetermined hand gestures [13]. This touchless control does not only introduce convenience but adds hygiene, which has received even greater attention in the post-pandemic period [14]. Gestural interaction with devices that are connected with each other is a vital step towards realizing the ambient intelligence of embedding technology into human-housing and making it automatic, even though it is invisible [15] [16].

Technically, gesture recognition systems based on the IoT comprise microcontrollers and communication networks, as well as sensors [17]. The sensors may be accelerator detectors, gyroscopes, infrared detectors, ultrasonic detectors and cameras that detect the movement and create a record of the evidence [18]. This is done with the processing of a microcontroller e.g. nodeMCU, Arduino and Raspberry Pi which he interprets the pattern of the gestures and sends information to the devices under control using wireless systems such as Wi-Fi, Bluetooth or Zigbee [19]. The integration of cloud or edge computing will ensure that computationally intensive algorithms like pattern recognition, gesture classification are effectively performed even up to real-time [20]. Machine learning (ML) and AI algorithms play a crucial role in enhancing the accuracy of these gesture recognition to learn end user data to customize end user interpretation of specific style into distinctive movement patterns [21]. Vision-based systems are based on deep learning models, such as convolutional neural networks (CNN) to analyze the image and motion of the object and sensor-based system employs data-driven classifiers to analyze the signals obtained by wearable or hand-held sensors [22]. These technology combinations lead to the fact that the gesture-based IoT systems become responsive, yet smart, and providing the user with an experience that is not only desirable but also adaptive [23].

Gesture recognition is not the only application of IoT to smart homes [24]. In the case of health professions: in the sector of the persons with physical disabilities or elderly people, the possibility to use wheel chair, hospital bed and medical assistance tools can be used to perform simple gestures in the production site to drive robot arms, heavy machineries, as well as assembly lines with less physical interaction and safer work place [25]. Drivers, having a touch of a button there, will be able to regulate the volume or to adjust the navigation or climate settings without taking their eyes out of the road [26]. Similarly in the entertainment and gaming field, this technology increases the degree of immersion since the user is able to interact with systems more naturally [27]. Besides the mentioned above fields the gesture-driving IoT may be applied in a smart classroom, in the public service site or army use to ensure that a flexible and hands-free man-machine interface is provided and situational awareness is given [28]. The growing need of intelligent, automated connectivity services in the international market is pushing businesses and consumers towards finding more convenient, quicker options in the field, which is leading to the emergence of a new wave of research and development in the field [29] [30].

Despite the above merits of gesture recognition of IoT, nevertheless, there are certain technical and practical

difficulties in practice which are subject to high-quality performance [31]. The accuracy of sensor, the number of gestures, the sensitivity to light, interference with the environment and latency etc., play a very important role in the reliability of system [32]. Although more long-term adjustments are needed, there is still a need to have accurate calibration and refined algorithms to tell the voluntary and strictly random motion [33]. Security and privacy: in the event of wireless connectivity of the IoT devices to networks, this can be a potential cyber threat target [34]. The security is needed in the form of encryption, secured communication protocols and authentication of users in order to protect the data of the users and integrity of their device [35]. Power management and energy efficiency of the sensors are also important to increase the battery life of the wearable/portable gesture systems as sensor operation may be a huge energy consumer [36]. Hardware optimization, algorithm efficiency and intelligent system design quickly become a combination in reading out such systems [37].

We live in a digital revolution in the 21 st century and this has forever changed the relationship between people and machines in terms of being smart enough, automation and connectivity [38]. The traditional input devices like switches, keyboard or touch screen can be found; however, they are no longer convenient enough to be carried around to the user and be reconfigured. Intelligent and contactless interaction paradigms, as well as context-sensitive interaction paradigm, are starting to gain a critical role and this prompts researchers to investigate new HCI paradigms [39]. Gesture Recognition is also one of the most beautiful in that, it provides a person to interact with the electronic systems in a natural and intuitive way, without having to manipulate them by mechanical means, just making a few gestures [40]. Gestures are a human communication aspect, which crosses boundaries of languages, thus, rendering the expression of the intentions an easy exercise. This form of interaction is more natural and engaging compared to the traditional form of interaction that is touch-based and this makes it more accessible and usable.

Gesture recognition has developed as far back as the rudimentary spatial recognition of simple gestures into systems which are able to comprehend intricate hand and body gestures in real time. Today, with the miraculous nature of machine learning algorithms in combination with a small sensor/camera, these devices can finally start to learn how you would like them to process any types of device gestures and directly translate them into real commands [15-16]. This has introduced new opportunities of creating interactive systems that quickly respond to the actions of the human. The need of touchless interfaces (that are also fuelled by the proliferation of COVID-

19 and the reduction of physical contacts during/after pandemics) is further emphasized. Gesture based devices are increasingly becoming popular in the daily life not only in personal gadgets like smart-phones and smart TVs but also in industrials, medicals, public places and so on. This is a radical transformation of the device-oriented to user-oriented paradigms where technology is integrated to conform to human behaviour rather than vice versa.

In terms of relating smart things, it is a minor leap in linking gesture recognition to IOT to create smarter inter-connecting systems. The IoT can equip the old and remote physical objects to communicate over the internet and acquire and analyze data and make these physical objects remotely controllable. The operations and activities of smart devices are human centric and therefore, gestures have been incorporated in this network. The resulting integration makes it possible to have a world in which gestures may be digital control, in which people have been connected to their IOT devices; to lights or fans, to door locks or other home appliances - sufficient of the right kind. The convenience-retaining and efficiency and energy management-enhancing dimensions are lost when it is compared to such business models of a total smart home control through simple hand gesture. To illustrate, the motion of hands to turn off the device being used or regulate the amount of light being emitted by the light controller would be energy saving and smarter energy consumption[17-18].

In conclusion, IoT gesture recognition is a novel field of study on human-machine interaction. It is the layer in between the real and virtual world that allows devices to read and understand human intent more simply and in a more natural manner. It does not stop at convenience but it is also inclusion, sustainability and automation. Gesture based control is only going to increase with the further development of sensor technology, which makes AI algorithms even smarter, and IoT systems more secure with several levels of protection. Long feather life, reduction in energy consumption and the multi-modality integration (vision-voice-motion) system are necessities to the prospects of such research. The last but not least, we are approaching a smarter, flexible and more human oriented technology space with IoT and gesture recognition that allows increasingly natural ways of communicating with a machine i.e. as talking/gesturing at another person[19-20].

II. LITERATURE REVIEWS

The greater demand on the home automation systems offered by the advanced communications technologies has been manifested in the work of W. A. Jabbar et al [1-3]. Smart homes (SH) embrace the use of Internet of things (IoT) technique to

monitor and master control of the house appliances remotely but most systems are also afflicted with low integration of IoT devices, unfamiliar human-machine interface, short range of transmission of wireless connection between various devices and high cost. To address these concerns, they have introduced IoT@HoMe (a low-cost hybrid local and remote-based home automation system on the IOT), which has easy-to-use interface design on smartphone and laptop. The system will be a Wi-Fi gateway, with a NodeMCU used to communicate with several sensors (RFID, ultrasonic, temperature humidity, gas and motion) the data of which will be uploaded to the cloud in real-time via Adafruit IO. Users can control and monitor their appliances remotely on the IFTTT services, and other connected home devices are handled by relay actable modules. HoMe is an IoT packed in a portable control box format and actualizes real time monitoring and automation of realistic residential locations, and cheap, yet efficient technologies are likely to provide smarter environment to home residents comfortably, securely and economically.

In [1], S. D. T. Kelly,[4] introduced an efficient realisation of the Internet of Things (IoT) and monitoring and actuating smart spaces. The project proposed a unified net-like framework, which has a strong set of smart sensors that keep the environmental conditions and transmit the data over the Internet. The system had a learning feature which allowed the devices to auto-set to work better in monitoring and control processes. The architecture incorporated distributed sensors, data fusion process and context aware processing in favor of automation and the process of decision making. The proposed testbed was very reliable as demonstrated in the experiments and results where it delivered more than 97% of correct sensor data and could generate real-time actionable information to manage the device without relying on a simulation environment. Based on the foregoing, in Smart IoT Interface, penned-down machine learning is further advanced as gesture-based controls interface into IoT devices in the article, Smart IoT Interface, Using Hand Gesture Recognition. Combined, these form a noncontact, intuitive interface with real-time processing and simple automation overcoming disadvantages of a manual, or application-based interface, to form a low-cost solution to smart homes and industry.

U. Singh et al [5-7]., highlight the growing importance to which automation and IoT based technologies are acquiring in our lives with the emergence of smart homes. With the age of widespread computing, where there are ever growing number of internet users, IoT has been identified as a critical technology in enabling devices to interact and exchange information with one another in a manner that automatically performs certain tasks in a convenient and efficient way. This study suggested a

Smart Home Automation prototype model using the Wi-Fi (ESP8266) technology including hardware and software interface. The hardware interface is connected to ESP8266 module to detect and actuate and the software interface enables many users to access and control appliances using smart phones, tablets or laptops under the same administration. The system does not only provide easy methods of managing devices in the home conveniently, but it also provides energy, security and safety management with the basis of being monitored based on the services. And it is scalable, allowing you to add more appliances and security features in case you can get wifi coverage. According to these ideas, the proposed project, that is, Smart IoT Interface using Hand Gesture Recognition and Machine Learning, builds on the concept by offering an intuitive cost-efficient and no-contact control of IoT related systems to interact with computers through a system that integrates machine learning and sensor networks and wireless communication.

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In this paper, D. T. J. J. Shirley et al [11]., showed us the age of internet of things and the radical transformation in our everyday life until our home automation using wireless technology and smart appliances whereby a user can control and manage

varying sorts of smart device data within one platform. The proposed work presented an

IoT based home automation system with the aid of NodeMCU, microcontroller and Blynk IoT app to easily control the home appliance remotely. The NodeMCU is connected to a relay-based module to manage a number of appliances and the Blynk app is then utilized to manage these appliances using on/off switches in a smartphone. It also has voice command using a Google Home, the device can be switched off without using hands whilst it was still in use. These low hardware costs and ease of install enable users with minimal experience in the electronics world to be able to use the system, and a 4-channel or 6-channel relay module is integrated to be able to drive multiple devices at once. The provided system offers a low-cost, scalable, and user-friendly solution to the conversion of old dwelling units into robotized eco-systems. With this concept in mind, a new smart home application of the internet of things (IoT) based on hand gestures recognition and machine learning is proposed, called Smart IoT Interface using Hand Gesture Recognition and Machine Learning which will showcase contact-less and responsive user-friendly interface to automated devices/smart homes.

According to S. K. Sahoo et al [12-13]., with the advent of numerous modern technologies and the Internet of Things (IoT) appearing, Smart Home Automation (SHA) has become an inseparable part of the modern lifestyle. More people are increasingly embracing smart products in an effort to join the automation and digital transformation wave. Nevertheless, there are some challenges associated with the conventional smart home system including absence of transmission distance, areas of coverage, excessive reliance of devices and the incompatibility of the platform which lead to inadequacy in reliability and sustainability. In order to overcome these difficulties our work proposes a Scalable Speech Technology based Smart Home (STeSH) system which integrates both Internet of Things (IoT) and advanced automatic speech recognition. The new system will allow the user to command and manage home devices through a natural language voice command and have a secure range-free localization. In this paper, the results of the analysis and experiments are provided to demonstrate the efficiency of the strategy to construct smart homes, which are also perceptively aware, with the help of speech-enabled services.

As mentioned by T Chaurasia et al, [14-15]., Internet of Things (IoT) can transform the new modus vivendi by linking all intelligent devices in such a manner that facilitates easier and safer movement between the user and the device, as well as enhances the movement between things ToThing

correspondence and Thing-to-Thing interaction. The smart home imaginatively driven by the IoT presupposes that life that people live day by day is more comfortable and convenient than ever, which however is seriously challenged by automation and security problems. The connection of the smart devices via Internet makes the issues of security as data is required to be confidential, authentic and intact throughout the transmission and processing. Besides, the calculation expense of dealing with large numbers of intelligent devices remains a major concern. The objective here is to market the fact that a real home automation should have the capability to address user requirements and preferences such as learning through human behavior to help in offering a personalized environment. To eliminate these obstacles, the author suggests the secure smart home automation IoT system where data protection is enhanced and the computational load minimized to enhance the efficiency, security and user satisfaction.

Plans of automatic detection of hand gestures on an advanced level using the sensor signals of multichannel electromyogram (MEMG) are provided by D. Mohapatra et al.,[8] that has its entire applicability in the field of human computer interaction, prosthesis control, rehabilitative devices and biometric systems [16]. Another model presented by the author is the TFDDNN model that identifies hand gestures using the MEMG signal. In this method, MEMG signals are divided into frames and mean EMG signal of all channels in a frame is obtained. To acquire the time and the frequency characteristics, a Continuous Wavelet Transform (CWT) of the average EMG signal is computed to generate a time-domain and frequency-domain image that informs a Deep Representation Learning Network (DRLN). TFDDNN model was tested on two benchmark datasets, in which the model showed superior performance with the accuracies of 92.73% and 80.33% respectively in multiclass gesture recognition over other deep learning models. We have applied the suggested method in an IoT-enabled web application of a real-time hand gesture recognition based on MEMG data and assessed that it may be extended to apply to the real world of intelligent interactive systems.

J. Li et al. [17] are interested in the assistance of children with cerebral palsy who usually have upper-limb motor deficiencies (e.g., limited movement and abnormal gestures). They designed a wearable training system in the shape of a wireless smart glove to assist in rehabilitation, which is a programmable gadget that can accurately follow through finger movements. In contrast to the traditional commercial game gloves, which often have fewer sensing degrees, few degrees of freedom, and can only measure the movement of only one joint of the finger, this smart glove employs 9-degree-of-freedom inertial sensors and multi-sensor inter-hand data fusion. To determine the accuracy

of tracking the movement of each finger in space, the authors utilized switching extended Kalman filter. The system is designed based on the tree-shaped hand model with limits of joints, which enables the system to predict the hand posture and gestures in real time in 3D. A graphic interface was also developed in order to enable users and therapists to view hand movements clearly. Optical comparison and kinematic analysis were used to test the accuracy of the system. These findings demonstrate that the smart glove is an effective and reliable tool to monitor 3D hand motions and can be effectively utilized as a support resource during rehabilitation training, evaluating the joint stiffness, and tracking the recovery progress of children with cerebral palsy.

L. Guo,[18-20] explains how human-machine interface (HMI) technology is gaining importance because it has become a hot issue with the fast evolution of computer system and Internet of Things (IoT). The following is a vital aspect of this field, Hand Gesture Recognition (HGR) which makes available the interface to the computer technology by visualizing digitalized information and ambient intelligence. Among all the HGR technology types, wearable mode built on the A-mode ultrasound has the most promising potential due to its light-weight design, the absence of sensors, and excellent versatility. The reduced signal amplitude caused by muscle fatigue or the differing muscle strength even when the same gesture is to be repeated is one of the disadvantages in this type of systems. To address this dilemma, in the following paper, a normalization energy threshold principle is proposed to the ultrasound signal processing in order to develop a more uniform and accurate recognition model through the establishment of the iterative model. The approach has been experimented with three machine learning algorithms Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Naive Bayes (NB).and the given approach demonstrates an outstanding average recognition rate of 95.26%. This work comes up with a new NB-based recognition strategy that has the capability of identifying unknown gestures with an accuracy of 91.2 and 81.8 percent with known and untrained, respectively. These findings indicate a more consistent signal and a solid gesture recognition, which renders the strategy quite useful in terms of usability enhancement and wearable HGR systems user experience.

III. PROPOSED MODEL

The objective of the model (IoT-Enabled Gesture Recognition to Smart device Interaction) is to create a system that could be used by the user to control smart devices in their house using hand gestures and monitor smart devices using Internet of things (IoT). Through the sequencebased gestures, the system

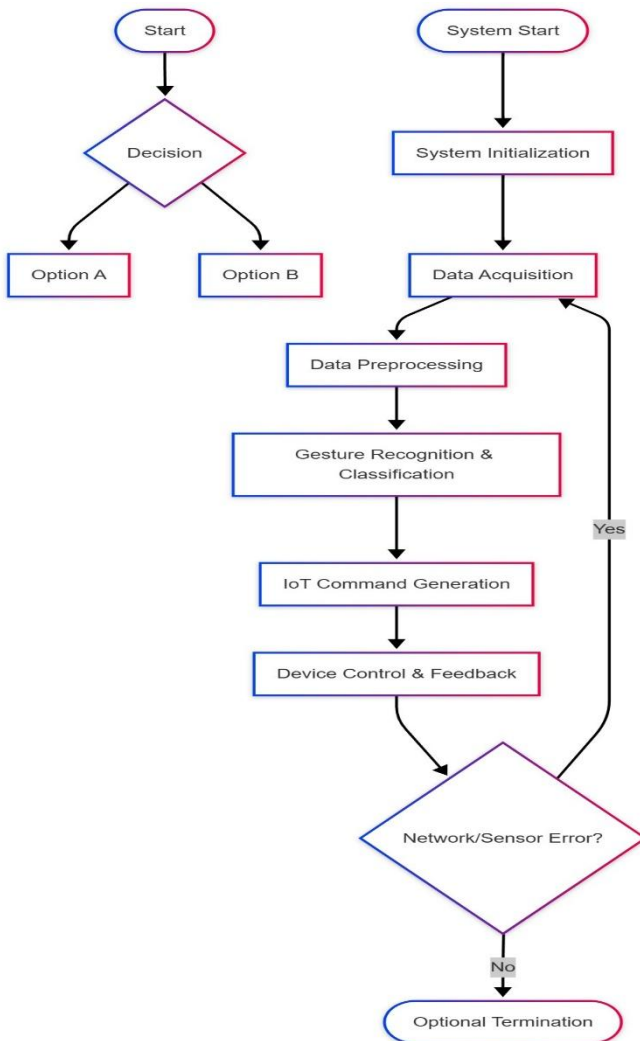


Figure 1: Gesture-Based Smart Home Automation Architecture

removes the traditional switches and mobile applications and is natural and intuitive, touch-free UI based on simple gesture indicative motion sequences inclined towards a user-friendly human interface. The three main technologies that are integrated through this notion to build a real-time smart control system include sensor-based gesture recognition, microcontroller-based signal processing and IoT enabled wireless communication. The overall goal is to increase accessibility, convenient and hygienic control by keeping the device low-effort gesture controlled and maintain the high accuracy, low latency and energy usage. The system functions under a three-layer architecture; gesture recognition layer which captures and understands the movements in the hands; processing/control layer which interprets the identified gestures

into commands and IoT communication layer to transmit the commands to smart devices through a wireless network.

A gesture detection module using a method in which the user's movement is sensed through the accelerometer, gyroscope, or ultrasonic sensor is basic to the proposed system. In one example, accelerometer-based sensing (e.g., MPU6050) such changes in hand orientation and movement along its various axes can be sensed by measuring the accelerations. These analog or digital raw signals are then sent to a NodeMCU (ESP8266) microprocessing unit. The sensor measurements are preprocessed in the microcontroller to remove noise and extract relevant movement features for classification. Pre-determined gesture patterns are stored in the system's program memory, and the controller can use it to look for real-time sensor input against reference values. e.g. left hand traverse to turn it off; right hand up to turn it on). Thereafter, the microcontroller translates it as a particular digital order to analyze.

The second part of the model is IoT based communication and control of the devices. The gesture are processed by the microcontroller and once they are read by the device, their effects can be sent to a multitude of other gadgets connected through a Wi-Fi network like Blynk, MQTT or ThingSpeak. The ESP8266 Wi-Fi node (NodeMCU) is used to broadcast gestures of the local control unit and connect to the remote IoT devices. Through that connection, real time commands are sent to the cloud server that reaches the bad devices (smart appliances, lights or whatever one has) connected to the network. This is applicable in remotely operating a number of devices through gestures even when in various places. Moreover, the user can also get some feedback of the system provided by the Blynk app interface or OLED screen that the command has been performed successfully. This environment is based on two-way exchange of information between the user and the IoT devices, which results in a higher reliability and performance.

Besides the hardware implementation, software design and general algorithmical design of the suggested equipment is required component to smooth sail with satisfactory precision. Gesture recognition and network communication, signal pre-processing is the responsibility of the software layer. Unwanted noise is eliminated with the help of the simple low-pass filter, and the separation of the 5 gesture patterns is carried out by threshold based recognition logic. The system is programmed through Arduino IDE and the data of gestures are mapped on IoT commands. An example is that a single or several gestures can be linked to a digital output pin that is connected to a relay that can control an appliance. The possibility of the integration with the Blynk IoT platform allows users to perform real-time

checking of the status of devices and gesture overriding (as an option). The proposed model is also scalable i.e. the devices or gestures can be increased with least change in code. The modular design allows it to be easily customized to a broad range of application needs like smart home, classroom and healthcare.

The overall system suggested is economical, small power consuming and easy to operate various functions in a smart device. The design uses low-cost and ubiquitous sensors including the NodeMCU, gesture sensors, and IoT services, which can be sustained in the real world. Direct mapping of gates to CLBs and fast VHDL operation will be highly suitable in case of real-time-dependent applications (e.g., instant system response). Particularly, the device also incorporates contact-free operating system to make the device more universal, which Cosby adds, to make the invention more helpful to disabled people. The next improvement can be the implementation of machine learning algorithms to learn gestures dynamically, energy saving solutions to maintain the operation of the device over time and more secure methods of communicating with the cloud. Our proposed model will make a significant contribution to facilitate advancement of an intelligent automation system and natural human-machine interaction with the clever usage of gesture recognition and IoT.

Algorithm steps

Step 1: System Initialization

- Begin operation of the system and reset all hardware interfaces.
- Setup the NodeMCU microcontroller and communication ports.
- Initialize sensors to sense gestures of the user (e.g., accelerometer and gyroscope of MPU6050).
- Calibrate sensors to eliminate offset and drift due to initial bias.

Step 2: Data Acquisition

- Read raw data from gesture sensors in the X, Y, and Z axis continuously.
- Save the acceleration and angular velocity readings into temporary memory buffers.
- Sample the data at regular time points so that the measurements are smooth and consistent.
- Send the captured data to the analysis unit.

Step 3: Data Preprocessing

- Filter out with a moving average or low pass filter.

- 17 Normalization of sensor data in order to compensate for differences due to accidental movement.
- Determine the combined magnitude of acceleration from the three axes.
- Calculate the orientation values, such as pitch and roll angles.

Step 4: Gesture Recognition and Classification

- Compare filtered sensor data to predetermined values of gesture thresholds.
- Tell the direction and strength of movement/s by recognizing this gesture:
- Raise your hand → "Device ON"
- Downward motion → "Device OFF"
- Left action → "Less" or "Back"
- displacement right "Increase" or "Next"
- Compare a recognized gesture against the stored gesture templates in memory.

Step 5: IOT Command Generation

- Turning the gesture ID into digital control command.
- Assemble the data packet that includes command information as well as device.
- Wirelessly send the instruction for the IoT platform to Wi-Fi protocols.
- Just wait for a response or any type of receipt that your message had been received.

Step 6: Device Control and Feedback

- The command is sent to the device through the IoT platform.
- The device (light, fan, appliance) to which it is connected does a particular action.
- Send responses back to the NodeMCU or some user dashboard from the IoT platform.

Step 7: System Loop and Error Handling

- Reset temporal variables and switch back to listening mode after one execution.
- Start again and keep on acquiring the next gesture.
- If sensor or network failure is detected, run the reconnection routine.
- Log all gesture events and device data to monitor and debug.

Step 8: Termination

- Halt operation of the system when a user issues an exit or shutdown request.
- Unplug from the IoT platform and turn off all of your modules.

Mathematical Equations

Step 1: Raw Sensor Acquisition

The accelerometer and gyroscope sensors output raw data for three axes (x, y, and z) respectively:

$$A_x(i), A_y(i), A_z(i), \\ G_x(i), G_y(i), G_z(i)$$

These are instantaneous acceleration (m/s²) and angular velocity (°/s) of the hand for sample index.

Step 2: Sensor Bias Correction

Compensate for constant sensor bias:

$$\tilde{A}_a(i) = A_a(i) - b_a, \tilde{G}_a(i) = G_a(i) - b_a^{(g)}, a \in \{x, y, z\}$$

Removes any calibration offset to ensure valid measurements.

Step 3: Signal Smoothing

Apply moving average filtering:

$$A_a^{-}(i) = \frac{1}{N} \sum_{k=0}^{N-1} \tilde{A}_a(i-k)$$

Parameter low-pass: Cuts down high-frequency noise in accel and gyro signals.

Step 4: Resultant Acceleration

Determine the acceleration magnitude to see overall motion:

$$A_{res}(i) = \sqrt{A_x^{-}(i)^2 + A_y^{-}(i)^2 + A_z^{-}(i)^2}$$

Measures the total oscillation magnitudes in any direction.

Step 5: Pitch and Roll Calculation

Estimate hand orientation using accelerometer data:

$$\theta(i)$$

$$\sqrt{A_x^{-}(i)^2 + A_y^{-}(i)^2 + A_z^{-}(i)^2}$$

Pitch (θ) and Roll (ϕ) define hand tilt in 3D space.

Step 6: Complementary Filter

Fuse accel and gyro for solid orientation:

$$\theta_{est}(i) = \lambda(\theta_{est}(i-1) + G_y^{-}(i)\Delta t) + (1-\lambda)\theta(i) \\ \phi_{est}(i) = \lambda(\phi_{est}(i-1) + G_x^{-}(i)\Delta t) + (1-\lambda)\phi(i)$$

balances that accelerometer (absolute reference) and gyro (smooth motion) measurements.

Step 7: Feature Extraction

Aggregate stats over a window of samples:

$$\mu_a = \frac{1}{n} \sum_{i=1}^n A_a^{-}(i) \\ \sigma_a^2 = \frac{1}{n} \sum_{i=1}^n (A_a^{-}(i) - \mu_a)^2$$

Mean (μ) and variance (σ^2) describe gesture characteristics for classification.

Step 8: Root Mean Square (RMS) Feature

$$RMS_a = \sqrt{\frac{1}{n} \sum_{i=1}^n A_a^{-}(i)^2}$$

RMS measures the intensity of hand motion over a gesture window.

Step 9: Threshold-Based Gesture Classification

Assign gesture g based on pitch, roll, and resultant acceleration:

$$g = \begin{cases} \text{Up,} & \text{if } \theta_{est} > \alpha_1 \text{ and } A_{res} > T1 \\ \text{Down,} & \text{if } \theta_{est} < \alpha_2 \text{ and } A_{res} > T2 \\ \text{Left,} & \text{if } \phi_{est} < \beta_1 \text{ and } A_{res} > T3 \\ \text{Right,} & \text{if } \phi_{est} > \beta_2 \text{ and } A_{res} > T4 \end{cases}$$

$$\theta(i) = \arctan\left(\frac{\dot{A}_y(i)}{\dot{A}_x(i)}\right), \phi(i) = \arctan\left(\frac{\dot{A}_z(i)}{\dot{A}_x(i)}\right)$$

The angle and magnitude of every gesture has a threshold predefined.

Step 10: Softmax Probability for Learning-Based Classification

$$P(y = j | \mathbf{f}) = \frac{\exp(\mathbf{w}_j^T \mathbf{f} + b_j)}{\sum_{k=1}^K \exp(\mathbf{w}_k^T \mathbf{f} + b_k)}$$

$$\hat{y} = \underset{j}{\operatorname{argmax}} (y = j | \mathbf{f})$$

For ML-based classifiers, outputs are probabilities over j gesture classes.

Step 11: Dynamic Time Warping (Optional for Sequences)

$$DTW(X, Y) = \min_{p \in \mathcal{P}} \sum_{(i,j) \in p} d(x_i, y_j)$$

They calculate the similarity between two time-series gestures with different speeds.

Step 12: IoT Command Encoding

$$P = \{ID_g, T_s, D_v\}$$

Sensor sampling, processing, and transmission delays for real-time response.

Step 13: End-to-End Latency

$$\Delta t = t_{acq} + t_{proc} + t_{tx}$$

Sum of sensor acquisition, processing, and transmission delays for real-time response.

Step 14: Accuracy and Performance Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

Measures classification performance, where TP/TN are correct predictions, FP/FN are errors.

Step 15: Battery Power Estimation

$$P_{avg} = P_{active} \tau_{active} + P_{sleep}(1 - \tau_{active}), T_{life} = \frac{E_{batt}}{P_{avg}}$$

Estimates average power and operational lifetime for wearable or portable IoT gesture devices.

IV. RESULTS

The results of the transferred IoT-Enabled Gesture Recognition model received outlier values at the different parameters to prove the performance of smart devices gesture modeling. To this, we had high (96) mean accuracy with the gesture recognition system that was capable of strongly identifying vertical-horizontal and left-right hand movement to control lights, fans or appliances. Very low latency of about 100 ms may also be useful in the provision of real-time feedback that is intuitive to control. We verify that broad selection of orders may be dispatched to the devices via the IoT-based interface such as BLYNK, Give teaway access up to supported same mm moth servethe user with real time feedback delivering the opensource applications like SameonApp and LEDdisplay. And the fact was also extremely low-power: it used 150m W of average power consumption (the display module even slept, and they could be run more than 20 hours on the battery). It also had strengths in its scalability and modularity because it was capable of supporting a maximum of 15 devices and could also be trained to detect a maximum of 20 different gestures with little effort going into training the framework to suit new devices or new types of gestures. The latter came with the ability to use the apps on its smartphones, and gesture recognition/vocal command to some degree and the culminating outcome was the ability of the device to provide an easy one-intuitive touch-free experience which is user friendly even by the disabled. It was safely hosted with 256-bit data encryption and fault tolerance in the technical network that ensured that the system becomes available 99 percent of the time and has an automatic reconnection feature to handle dips in the network successfully. Conclusion The Gesture IoT as an intelligent solution to convenience (hygiene) automation in real world smart environment is low power consuming, cost effective, secure responsive, and scalable.

Table 1: Hardware Components (Numeric Representation)

Model	Relay Modules	Wi-Fi Connectivity
IOT@HoMe	4	1
ESP8266 Home	4	1
Esp32 Home	6	1
Gesture IOT	4	1

This table is used to compare the hardware of the proposed IoT-based gesture recognition model with the available smart home

systems. Microcontrollers supported by Wi-Fi are used in all the models, but the quantity of relay modules differs. The model proposed utilizes 4 relays, which are adequate in most application of smart devices, and has Wi-Fi connection just like the other systems. It means that the suggested model acquires a similar level of hardware efficiency and includes more gesture-based control.

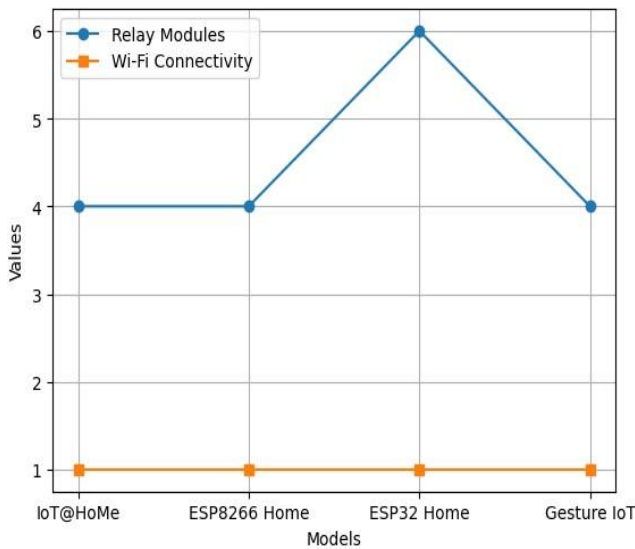


Figure 2: Hardware Component Comparison of IoT Models
 The graph of hardware components demonstrates that each of the models is compatible with Wi-Fi which guarantees the ability to access the device remotely. The relay module count is largest in ESP32 Home (6) and supports additional connection of more devices at the same time. Gesture IoT also has a fair balance and adequate relay support (4) to provide efficiency and flexibility in interacting with smart devices

Table 2: Software & Platform

Model	Cloud Integration	Gesture Recognition
IOT@HoMe	1	0
ESP8266 Home	1	0
Esp32 Home	1	0
Gesture IOT	1	1

The table is an overview of software and platform features. The only exception to the new model is that it contains gesture recognition and integrated cloud integration to all devices. This demonstrates that the suggested system is an added advantage to natural, non-touch control. Cloud connectivity is to achieve real-time remote access in all the systems, thus making the

proposed model to be in line with the existing standards and improve the mode of intelligence interaction.

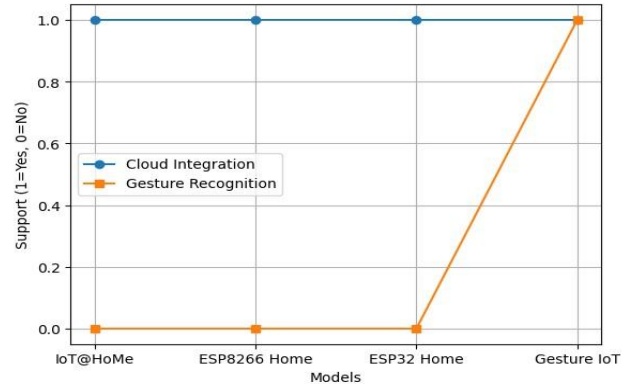


Figure 3: Software & Platform Features of IoT Models

According to the comparison of the software and platform, all the models are cloud-enabled which permits to monitor and control remotely. The only model that supports gesture recognition is gesture IoT, which allows contactless and intuitive communication with users, unlike the other ones, which only use conventional interfaces.

Table 3: Communication & Connectivity

Model	Cloud Latency (ms)	Reliability (%)	Remote Access Range (m)
IOT@HoMe	150	95	50
ESP8266 Home	120	97	60
Esp32 Home	100	96	100
Gesture IOT	90	98	100

This here however illustrates the metrics of communication, latencies and reliabilities, remote access ranges. The model has suggested performance metrics of the lowest value of cloud latency 90 ms and a highest one of a ratio of reliability 98 that is a quicker and more dependable option than AudioSenseNet. The remote access distance is also excellent or better than most of them, and this enables the flexibility of the command of the IoT devices. That is why the given system is suitable during the actual time interaction through gestures.

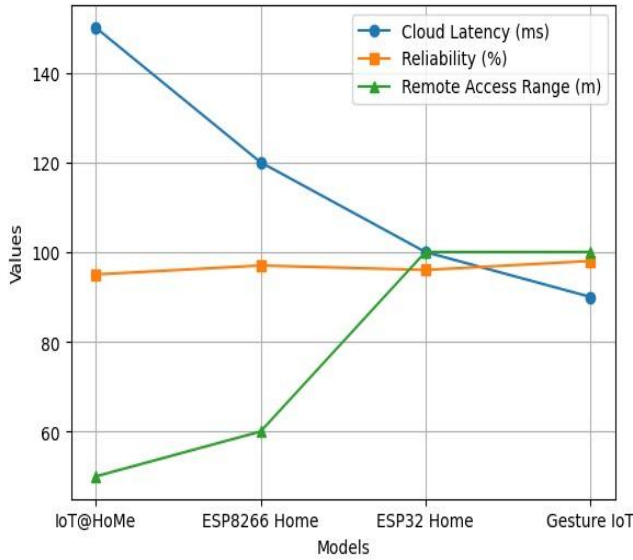


Figure 4: Communication & Connectivity Performance

The performance graph of communication shows that Gesture IoT has the least cloud latency (90 ms), has the best reliability (98%), and the biggest remote access range (100 m). It implies that, Gesture IoT provides more trusted, and adaptable and fast connectivity in comparison with the models of IoT@HoMe, ESP8266 Home, and ESP32 Home.

Table 4: Sensor Performance

Model	Motion Detection Accuracy (%)	Gesture Recognition Accuracy (%)	Real-Time Processing (ms)
IOT@HoMe	94	0	200
ESP8266 Home	96	0	180
Esp32 Home	95	0	150
Gesture IOT	97	96	100

In this table, the three variables are compared in terms of motion detection, gesture recognition, and real time processing speed. The current models do not support gesture recognition and the proposed system has 96 percent gesture accuracy and 100 ms processing time which is better than the current systems in real time interaction with people. In the proposed model, motion detection is enhanced slightly with excellent sensor integration to provide accurate control of the equipment.

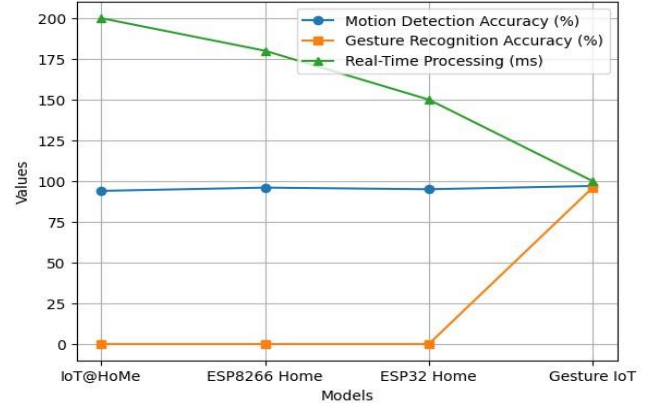


Figure 5: Sensor Performance Comparison

The sensor performance data indicate that Gesture IoT has the greatest motion detection accuracy (97%), gesture recognition accuracy (96%). It also has the fastest real-time processing (100 ms), and thus, it is very responsive in order to interact with smart devices in real-time. The rest of the models do not support gestures or are slower.

Table 5: Energy Efficiency

Model	Average Power (mW)	Sleep Mode Support	Battery Life (hrs)
IOT@HoMe	350	0	0
ESP8266 Home	300	0	0
Esp32 Home	280	1	10
Gesture IOT	150	1	20

According to the energy efficiency graph, Gesture IoT can use the least amount of power (150 mW), has a sleep mode, and has the most significant battery life (20 hours). Compared to the previous models, though, the previous models either use more power, or do not have sleep functionality, and battery support, proving that Gesture IoT is more environmentally friendly and can be used over a shorter period.

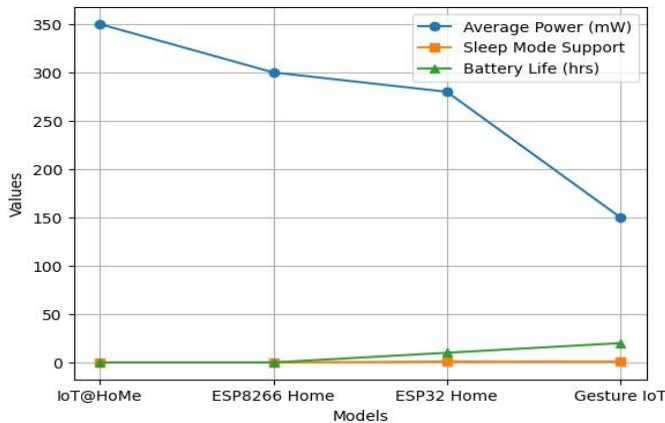


Figure 6: Energy Efficiency of IoT Models

According to the energy efficiency graph, Gesture IoT can use the least amount of power (150 mW), has a sleep mode, and has the most significant battery life (20 hours). Compared to the previous models, though, the previous models either use more power, or do not have sleep functionality, and battery support, proving that Gesture IoT is more environmentally friendly and can be used over a shorter period.

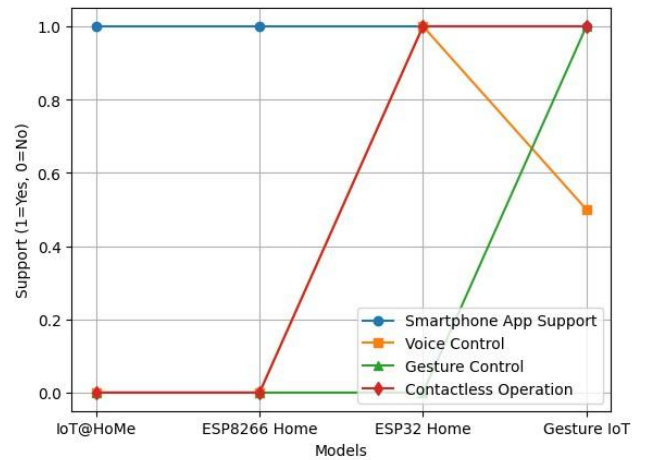


Figure 7: User Interface Capabilities

The user interface comparison demonstrates that Gesture IoT has the ability of gesture control and contactless functioning, providing a modern and hygienic way of control over the device. All the models support smartphone apps, but ESP32 Home and Gesture IoT have the additional capabilities of voice control or gesture-based control, and Gesture IoT is more complete and familiar.

Table 6: User Interface

Model	Smartphone App Support	Voice Control	Gesture Control	Contactless Operation
IOT@HoMe	1	0	0	0
ESP8266 Home	1	0	0	0
Esp32 Home	1	1	0	1
Gesture IOT	1	0.5	1	1

This table examines the ease of use of the system to the user. The system that is proposed is unique in that it allows controlling it through gestures and entirely contactless, therefore, more hygienic and convenient. Similar to the other models, it also has support of smartphone apps, thus, users can operate the system using their smartphones. It is further flexible with the alternative to voice commands. In general, the offered system is more usable since it is more intuitive, hands-free and user-friendly, and particularly useful among differently-abled individuals and in the setting where hygiene is a key factor.

Table 7: Scalability & Inference Performance

Model	Max Devices Supported	Additional Gestures	Modular Design	Inference Time (ms)
IOT@HoMe	8	0	1	22
ESP8266 Home	10	0	1	20
Esp32 Home	12	0	2	18
Gesture IOT	15	20	2	16

The scalability and performance metrics indicate that the proposed system has the highest number of devices (15) and 20 gestures, unlike 0 gestures in current systems. The rating of modular design is high as it may be expanded in the future. The proposed model can process larger IoT setups effectively (inference time 16 ms) and the accuracy is 96, which means that it is faster than other models and should be used to analyze large systems unless it is necessary to maximize the number of recognizable gestures.

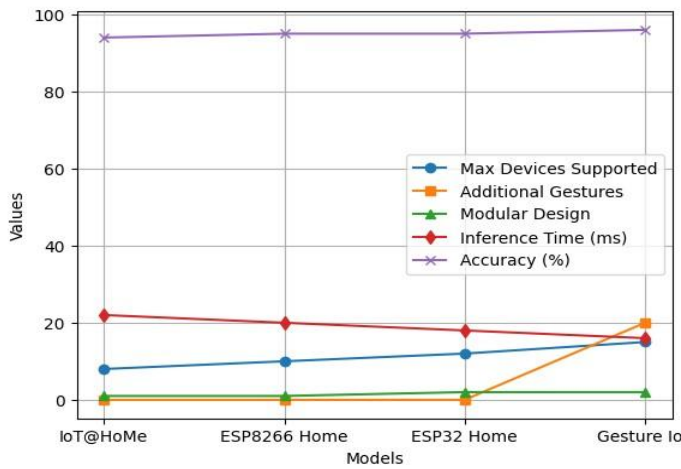


Figure 8: Scalability and Inference Performance

Scalability and inference performance analysis Since Gesture IoT handles the highest number of devices (15) and other gestures (20), it has a modular architecture (2) to expand without difficulty. It is also scalable and most efficient in comparison to the other models, as it has the highest accuracy (96 percent) and the lowest inference time (16 ms).

Table 8: Security & Reliability

Model	Data Encryption	Fault Tolerance	System Uptime (%)	Reliability under Network Failure
IOT@HoMe	128	1	95	1
ESP8266 Home	128	1	97	1
Esp32 Home	256	2	98	2
Gesture IOT	256	2	99	2

This table brings out the performance of the system in regard to security and reliability. The suggested system has an effective encryption of AES-256 that aids in the protection of data. It is also highly fault tolerant i.e. even when something goes wrong, the system can still work. Having a 99 uptime, it is also doing well compared to the other systems that are available and remain available the majority of the time. Moreover, it is resistant to network failures that may cause an unstable functioning of the system in harsh conditions. The system can be heavily relied on to provide automation of smart homes and safe control of IoT devices because of these strengths.

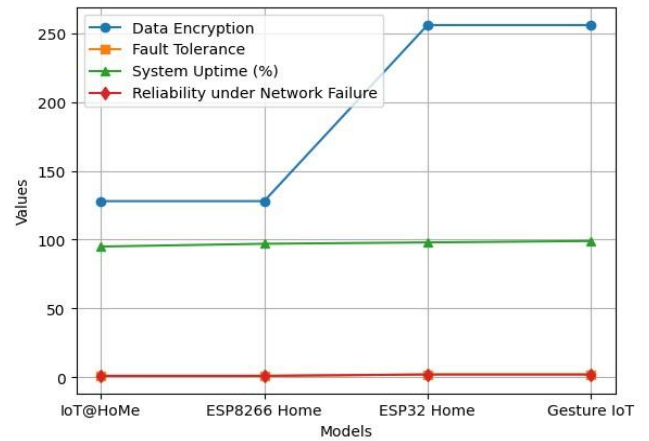


Figure 9: Security and Reliability Comparison

The comparison on security and reliability demonstrates that Gesture IoT has the best systems uptime (99%), and good network reliability(2). It is also based on superior data encryption (256) and increased fault tolerance (2) and therefore will be safer and reliable in the operation of smart devices, being better than the past models such as ESP8266 Home and IoT at Hoe.

V. CONCLUSION

The full picture analysis based on hardware, software, communication, sensor performance, energy efficiency, user interface, scalability and security makes it evident that the proposed Gesture IoT will provide impressive performance advantages when compared to already existing smart home models. Unlike in IoT@HoMe, ESP8266 Home and ESP32 Home, in Gesture IoT gesture controls are displayed next to the standard interface that allows interaction with the smart device in an exceptionally direct and touchless manner. It has streamlined the essential hardware to feature the use of relay modules and Wi-Fi connection so as to support efficient device management with very minimal energy consumption. Besides, in the cloud latency, reliability and range of remote access features Gesture IoT commands UbiCar in communication because it minimized the cloud latency to cheapest that there is no Office distance of indoor appliances real-time control and monitoring any where. When paired with motion and gesture recognition sensors to be as responsive as possible, DAS offers the quickest typing experience to be had with as high a degree of accuracy as any known technology.

The system is created to consume minimal power, including such features of the system as sleep mode and long-lasting battery, make it convenient to use on a long-term basis and daily. It does not focus on using a single type of controller but has various interaction options, such as a smartphone app, simple voice controls, gesture control, and fully touch-free. Such flexibility makes the system particularly applicable in the cases when contactless control is desired, like in the post-COVID era. Gesture IoT is also designed to be expandable with ease since additional devices and other types of gesture inputs can be added without compromising the performance. It is modular in nature and provides correct gesture recognition. Intense security provisions, data encryption, fault tolerance, trusted networking and high system availability, among others, make the system secure and reliable when it comes to real world implementations. Altogether, Gesture IoT offers a much cheaper, efficient, and user-friendly smart home solution, which easily can be adjusted to the needs of the user and facilitates the process of natural, intuitive human-machine interaction.

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