Gesture Driven Smart Home Solution for Bedridden People

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ABSTRACT

Conversion of ordinary houses into smart homes has been a rising trend for past years. Smart house development is based on the enhancement of the quality of the daily activities of normal people. But many smart homes have not been designed in a way that is user friendly for differently-abled people such as immobile, bedridden (disabled people with at least one hand movable). Due to negligence and forgetfulness, there are cases where the electrical devices are left switched on, regardless of any necessity. It is one of the most occurred examples of domestic energy wastage. To overcome those challenges, this research represents the improved smart home design: MobiGO that uses cameras to capture gestures, smart sockets to deliver gesture-driven outputs to home appliances, etc. The camera captures the gestures done by the user and the system processes those images through advanced gesture recognition and image processing technologies. The commands relevant to the gesture are sent to the specific appliance through a specific IoT device attached to them. The basic literature survey content, which contains technical words, is analyzed using Deep Learning, Convolutional Neural Network (CNN), Image Processing, Gesture recognition, smart homes, IoT. Finally, the authors conclude that the MobiGO solution proposes a smart home system that is safer and easier for people with disabilities.

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KEYWORDS

Deep Learning, Computer Vision, Gesture, Smart Appliances, Internet of Things

1 INTRODUCTION

In previous years, Home automation Systems have attained great interest in making life more convenient and more comfortable for people. The term Smart Home is used to describe a house that uses internet-connected devices to enable the remote monitoring and management of appliances and systems such as lighting and heating. The home automation system, which is also called smart homes and connected home, provides homeowners with convenience, safety, and energy efficiency to control smart devices, part of the Internet of Things (IoT), smart home systems and devices also work together, exchanging customer usage data among themselves and automating homeowner preferences-based actions [1]. Working concept of various types of home automation systems such as Dual Tone Multi-Frequency (DTMF)-based, Global Mobile System (GSM)-based, speech recognition-based, Zigbee-based, Bluetooth-based, Internet and Wi-Fi-based, and home automation solutions based on Gesture was studied [2]. One of the common advantages of home automation is domotics that is useful to the disabled, providing supervision that can support them live comfortably and safely at home, rather than going to a retirement home or seeking 24/7 home care. Smart home systems, however, have failed to become popular, in part because of their technical nature. The apparent complex nature is a drawback of smart homes; some people struggle with technology or will give up on it with the frustration. In home automation systems, machine learning (ML) and artificial intelligence (AI) are becoming extremely popular, allowing for home automation implementations to adapt to their environment.

Disabled people like immobile, bedridden people are the ones who need a smart home solution, but they are the category of people who are least addressed in this matter also. Therefore, this focus of this research is on these people. Immobile, bedridden people face many difficulties while doing their day to day activities and even if they get a smart home, they face difficulties while giving commands to the smart homes. Generally, smart homes are designed for people who are not disabled or not handicapped due to various illnesses and locomotive problems. But for the report of the World Health Organization, about 15% of the world's population lives with some form of disability, of whom 2-4% experience significant difficulties in functioning [3]. Elderly people and People with disabilities like immobility, paralysis, deaf and dumb face many difficulties while trying to adapt to this kind of normal smart homes that have not been designed in a way that is user friendly for differently-abled people.

A smart home solution has been developed where the home is controlled via a mobile device [4]. The main drawback of this solution is that the technical knowledge of the user is compulsory. The mismatch of technical knowledge of the young generation and the elderly people gap. And also, elderly and disabled people with the inability to read and do subtle things like touching small buttons on the mobile screen. So, this solution is not compatible with every type of user. "A Smart Home Control System for Physically Disabled People" [5] has proposed a voice-based approach to control home appliances. The main drawback of this solution is that disabled people like dumb people face difficulties due to the inability to speak to give a command to the system [6]. Another smart home solution has been developed which is driven by gesture capturing sensors (Kinect) [7]. The main drawback of this system is that the object detection distance of the sensors is limited. And also, the sensitivity of the sensors for sunlight is high so gesture detection may not work properly. Neither mobile-driven smart home nor voice-driven smart home doesn't accomplish every aspect of people including differently-abled people. Although sensor-driven smart homes are better than the previously mentioned smart home types, it is not user friendly for disabled and elderly users. The necessity for bedridden patient-friendly, smart home system rises. To fill this gap, a visual-based gesture-driven smart home system; MobiGo is proposed.

2 LITERATURE SURVEY

2.1 Gesture Recognition through Camera

There are many types of gestures that can be used to give commands to a smart home but when we consider our target users who are immobile and bedridden people, very few are compatible. The main types of gestures are static gestures where one frame of the gesture is compared. The other type is dynamic gestures where a frame sequence of a specific gesture is taken in [20]. Complex hand movements as gestures are difficult for the immobile, bedridden patients. The static gestures are selected as the primary type of gesture inputs of this system.

A study on Continuous gesture recognition by using gesture spotting has developed a gesture recognition algorithm that extracts meaningful gestures in an online situation [6]. The start and endpoint of the target gesture are identified using a stand-up posture as stand posture is easy to detect. The start and endpoints are set to detect if a person is stood up. Posture detection is done using skeletal joint information. 10 frames are collected at the start to check whether the posture is stood up using the skeletal joint information. If 70% of the frames are detected as stood up posture, the posture is confirmed as the starting point of the gesture. After the starting stand up posture detection every 10 frames are saved until the system detects the ending standing posture. Motion History Images (MHI) are used to save motion from different views and a Histogram of Oriented Gradients (HOG) is used to normalize the gradients of the grayscale image [6]. As the target users of MobiGo is bedridden and immobile, this algorithm needs to be improved for it to be user friendly with the bedridden patients. Figure 1 illustrates the average test accuracy of the study is 97.3%.

Gesture Type	Accuracy (%)		
	Front MHI	Front / Right MHI	Front / Right / Left MHI
Up	92.5	97.5	97.5
Down	94	98	98.25
Move forward	91.75	92	93.5
Move backward	93.5	96.75	98.25
Move left	100	100	100
Move right	99.25	100	100
Welcome	98.5	98.75	98.25
Agree	97	96.75	97
Disagree	98.25	99.25	99.75
Love	96.75	97.75	97.75
Total	96.15	97.68	98.03

Figure 1: [6] Test Accuracy

"gesture recognition system that detects fingertips of the hand" [8] captures the hand gestures in real-time via camera. First, the hand region alone is segmented using an algorithm that develops region followed by morphological operations. The centroid of the palm region is calculated and the fingertips are then detected using the convex hull algorithm. The video of YUY2 format is converted to an RGB bitmap format and then the individual frames captured are converted into grayscale images. Then the region growing algorithm and morphological operations are applied. Convex hull algorithm is applied to identify the fingertips of the hand. The distance between the center of the hand region and a pixel in the convex hull set is calculated. If the distance of the radius of the hand is longer, the hand is identified as the spread and otherwise, the fingers are identified as are folded. It identifies the lengthiest vertex as a pointer finger.

A hand gesture recognition system has been developed that uses the pre-trained Artificial Neural Network (ANN) for the classification [9]. The gesture recognition process is categorized into 3 main stages as hand shape recognition, tracing of detected hand (if dynamic), and converting the data into the required command. Each frame of the video of the gesture is resized and padded and then entered to the classifier. If the classified hand is static (human gesture) immediately passes to the second step which is the hand tracing stage. For hand shape recognition, the classifier is trained through the process of transfer learning over pre-trained CNN. Transfer learning is transferring learned features of a pre-trained network to a new problem. The proposed CNN network consists of 13 convolution layers including 3 fully connected layers. The study has gained a test accuracy of 93.09%.

2.2 IoT Device for Smart Home Appliances

Design and Implementation of Smart Socket Prototype Controlled by Android Application [6] have a Smart Socket prototype for the calculation of electrical power in a rental house, which aims to provide a solution to the problem of the inequality of electricity use between rental home residents. Here they used hardware aspects as the ESP-12E Wi-Fi Module [7], as the IoT application module it can deploy in domestic automation, home appliances, industrial wireless network, fields of sensor networks. Relay for 30A volt 220-250 which is a switch powered by the use of electric power. Relay is an electromechanical device that consists of two main components, namely the electromagnet (coil) and the mechanical (switch). Smartphone with Android OS 5.0 (Lollipop) is a Linux-based mobile device operating system that includes operating systems, middleware, and applications. Android provides developers with an open platform for creating an app. They used aspects of the software as the Arduino IDE software is used to write down the code for running a system. Cloud Storage is an architecture of information technology, in which storage resources are available as Internet-accessible services. Cloud storage supports business processes using Internet-based services. Android Studio Software is an Android platform-based application development IDE. Android Studio is designed to make it easier for developers to build Android apps using JavaScript. The main drawback here is to obtain total power information and send socket status information, which includes the address of the destination server. But at its low cost, low power consumption capacity, as it requires 3.3V power, built-in Wi-Fi module, integrated TCP / IP protocol stack, easy to flash, and erase the firmware, the module is best suited for the Internet of Things (IoT) and is powered by use.

A study on Integrated Smart Plug Design [8] have developed Smart Plug using Arduino as a control system for setting on and off conditions, as well as monitoring the voltage, current, and power connected to the Bluetooth module as a communication system between Arduino and Raspberry Pi which serves as a webserver and data communication center. Use hardware such as Arduino Nano, Bluetooth module, Relay module, ACS712 current sensor, and ZMPT101B voltage sensor, Smart Plug model Here the web page design section on the server-side is addressed to show the data sent by Arduino and to store the data in the Raspberry Pi 3 database, the monitoring page for each parameter that the user can access to see the data sent in real-time. Web pages built using the Node-RED programming of the Internet of Things (IoT) the study was carried out using Arduino Nano, Relay 1 Channel 5V Module, and Arduino IDE software. During testing and implementation, the conclusion was reached that the data sent is obtained and stored in the database, the monitoring page shows data readings and regulates the flames and die electrical devices. It is known from the design results that the module can conduct data transmission, view the monitoring page, and do the control and accuracy of current readings obtained between 91.50 percent to 99.61 percent and the accuracy of the voltage readings obtained ranges from 98.95 percent to 99.90 percent. This system is highly versatile and cost-effective, both for sensor form and number of

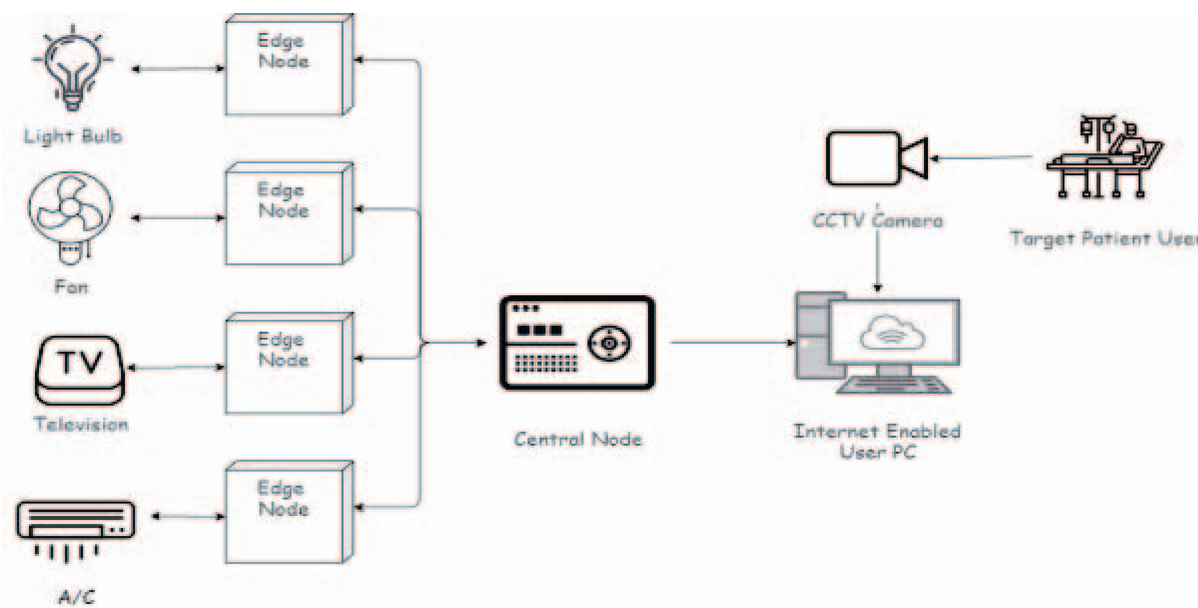

Figure 2: Figure 3: System Architecture

sensor nodes. It is therefore ideal for a wide range of environmental monitoring applications.

3 DESIGN AND IMPLEMENTATION

The main objective of this research is to implement an effective solution: MobiGo in aid of immobile people in their domestic life. Smart home solutions have become a convenient system for everyone in their day-to-day activities. As the existing solutions don't cover every aspect of smart home solutions for immobile people, a new gesture-driven solution for the immobile people is implemented. Figure 3 illustrates the overall system architecture diagram of the proposed system. The target user is the bedridden patient and the gestures are capturing through the camera as illustrated in the diagram. The video captured by the camera is sent to the central node and performs the main three gesture recognition steps. They are gesture detection, gesture extraction, and gesture recognition. When the central device identified the activity as the gesture after several runs through the CNN model gesture recognition, the central device will perform the relevant command according to the gesture. The switch of the electric device will be switched on or off according to that command.

3.1 Convolutional Neural Network (CNN) Model

For this proposed system, the dataset creation for the CNN model training and testing is done using a combination of gesture images from both the left hand and the right hand. A combination of varying depths where the hand is located is considered. The images are being resized during the preprocessing phase. 6 basic gestures with a total of 12000 images, have been pre-defined and added to separate directories with specific labels. The basic gesture types are mentioned in Figure 4 (a).

The dataset is then partitioned into portions as for training and testing. We have given 80% and 20% of the dataset to training and testing, respectively. Here Convolutional Neural Network (CNN) is used as the image classifier. The efficiency of the proposed system is based on the collected dataset. The dataset contains various hand orientations and depths as depicted in Figure 4(b). Different depths are used to give more variance to the dataset as the location of the bedridden patient can vary from one patient to another. And the hand orientation is also taken into consideration as the bedridden patient might not be able to pose the gesture as a stood-up person. As the bedridden patients and elderly people might face difficulties while posing the gesture, the variation of the different gestures in the dataset is utilized. Hence, the accuracy of the model has increased.

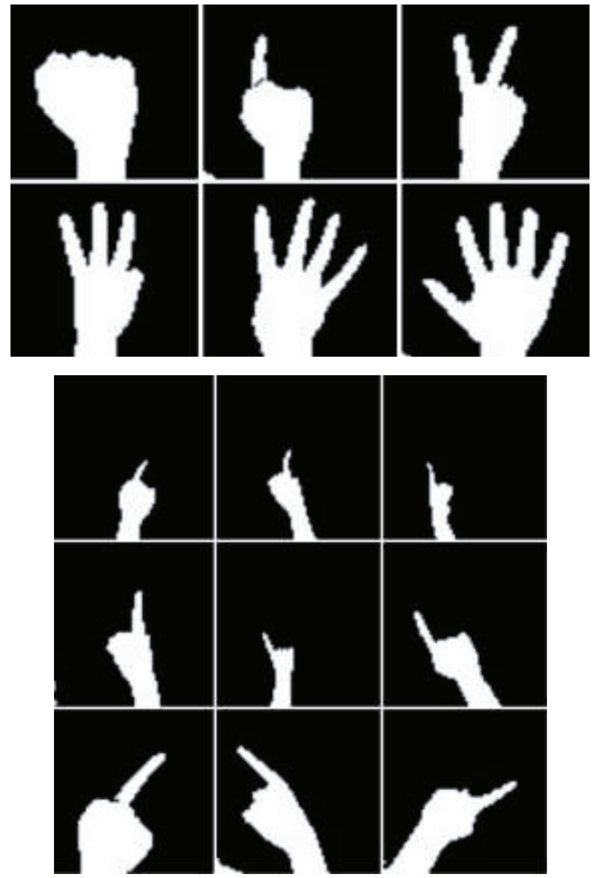

Figure 4:(a) Basic Gesture Types used. (b) Different Gesture Variation

The convolutional layer performs the cycle of convolution between the feature map and one convolution kernel. 3 layers of convolutional neural networks have been used here. The input image size is set to 64pixels. Then the max-pooling is set. Pooling layers in CNNs summarize and downsample the outputs of neighboring groups of neurons in the same kernel map. After the convolutional layer and pooling layer, the feature maps of 2D images are connected as the 1D feature maps used for input of a fully-connected network. The output of the last fully-connected layer is fed to a softmax which produces a distribution over the 6 class labels. The model contains 3 Convolutional layers and 2 Max Pooling layers along with 2 fully connected layers. Figure 5 displays the Model Summary of the proposed CNN model.

After the model structure is defined and compiled, the dataset is being imported and rescaled just in case of a size mismatch. The horizontal flip mode is enabled so that more variation is added to the dataset. The training set and testing set is separately imported with a defined batch size to be processed. Then it fits into the model and the number of epochs and number of steps of the training phase and validation phase is then defined. 50 epochs are used here with 6000 steps for training and 3000 steps for testing. The CNN model is set to save the best performance every time the model is trained.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 62, 62, 32)	320
max_pooling2d_3 (MaxPooling2	(None, 31, 31, 32)	0
conv2d_5 (Conv2D)	(None, 29, 29, 32)	9248
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 32)	0
conv2d_6 (Conv2D)	(None, 12, 12, 64)	18496
flatten_2 (Flatten)	(None, 9216)	0
dense_3 (Dense)	(None, 128)	1179776
dense_4 (Dense)	(None, 6)	774

Total params: 1,208,614
Trainable params: 1,208,614
Non-trainable params: 0

Figure 5: CNN Model Summary

3.2 Gesture Recognition through Camera

As the ordinary gesture recognition algorithms are designed for ordinary people with no disabilities and inability to move [11]-[14], there are not many smart homes developed with the help of camera-based gesture recognition. The gesture recognition sensitivity is not enough for the target users' sensitive gestures to be captured. Normally the input for gesture recognition is given through a wearable data glove [15]-[18] or a camera [11]-[13],[19]. As our target users are immobile, bedridden patients, requesting them to wear a data glove all day to give commands is not user friendly. The necessity for an improved gesture recognizing system compatible with bedridden people arises. An improved gesture recognition algorithm is proposed which is sensitive enough to recognize the gestures done by immobile patients who have a limited range of mobility when compared with normal people. The gestures are to be predefined. A Neuro Physician is consulted to specify the possible gestures for our target users. A camera is used to capture the gestures done by the user and the system processes those images through improved gesture recognition and image processing technologies.

Figure 6: Hand Detection and Background Subtraction

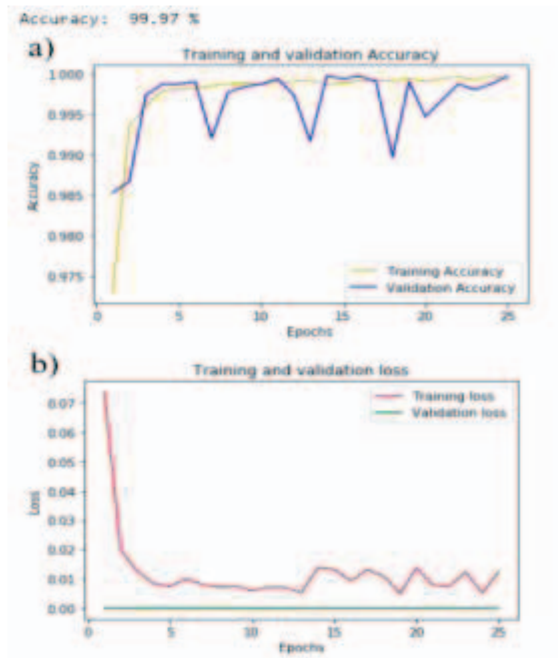

Figure 7: (a) Model Accuracy & (b) Model Loss

For recognition and prediction of the hand gestures, the video frames captured by the camera are first preprocessed. The frames of the video are first resized to the input size of the images fed into the CNN model. Hand tracking using the CamShift algorithm is not applied due to the drawback of capturing unnecessary background objects like a hand. The background subtraction function provided by OpenCV is used to extract the moving foreground mask and segment the hand. This method is used to track the movements and segment the specific object. Gaussian Mixture-based Background/Foreground Segmentation Algorithm is used to provide better adaptability to different illuminations and varying scenes. The region of interest is not defined as the patient’s position cannot be pre-defined.

3.2 IoT Device and Central Controller

For the implementation of the socket Arduino board and the two-channel relay are used. These two components are connected by pulling a jumper wire from the VCC port on the two-channel relay to the 5V port on the Arduino board. Another wire from the ground port (GND) of the two-channel relay to the ground port of the Arduino board. Input 1 (IN1) in the two-channel relay should be connected with the port 5 on the Arduino board. And also connect a jumper wire from input 2 (IN2) in a two-channel relay to port 4 on the Arduino board. This shows how the Arduino board and the two-channel relay are connected.

Connecting the HC-05 Bluetooth module and the Arduino module is the other part of the socket implementation. To supply power to the Bluetooth module, the Vin port and the ground port of the Arduino board should be connected with the Bluetooth module using two jumper wires. To transmit command from the Bluetooth module to the Arduino board, two ports (0-1) from the Arduino board should be connected to the HC - 05 Bluetooth module using two jumper wires.

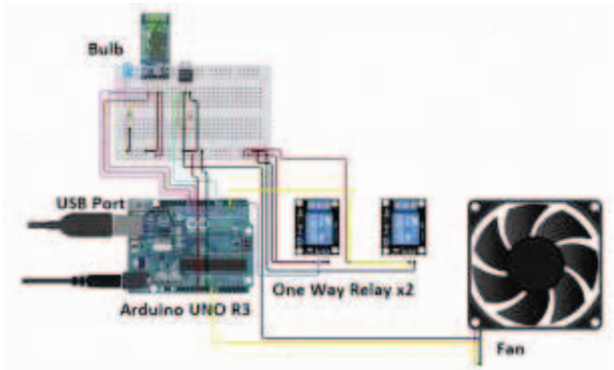

Figure 1*:* IoT Device Circuit Diagram

To connect the bulb with the module, one wire from the bulb should be connected with the NO1 port in the two-channel relay. Then COM 1 port of the two-channel relay should be connected with the power supply unit. To connect the USB port with the module, the port NO2 of the two-channel relay should be connected with the USB port and the COM2 port should be connected with the power supply unit (230V). Another node that comes from the 230V port should be connected with the bulb and the USB port. To connect the 12V USB fan with the module, one node of the fan should be connected with the No 6 port at the Arduino board using flexible wires. Another node of the fan should be connected with the ground port (GND) of the Arduino board. Finally, the power is supplied to the Arduino board using a USB cable.

When the system is implemented successfully, it should be connected to the power supply unit which has 230V current. The gesture recognition component identifies the gestures and then the python controller converts it to digital signals (0-5) according to the gesture and sends it to the socket. The socket will identify the relevant gestures and perform tasks according to the gestures. This simple theory works the entire system. The socket will perform any task within 100m inside the home.

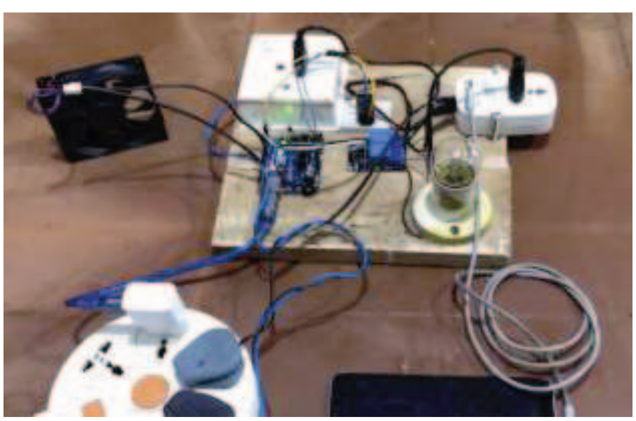

Figure 2: IoT Device Overview

RESULTS AND DISCUSSION

To recognize hand gestures and perform the background subtraction algorithm, gestures are captured by the computer embedded web camera of 1280x720 pixel resolution. The Watershed algorithm was proposed to be used for hand segmentation. But due to the unnecessary object detection, the algorithms were replaced by the in-built background subtraction algorithm offered by OpenCV which is capable of detecting only the objects in motion which is an advantage to detect only the hand segment of the bedridden patient. The need for object tracking algorithms like the CamShift algorithm was excluded making the hand gesture recognition simpler and more robust. As Deep Learning-Based programs need a higher computation power, the proposed system provides a light-weight software that can be installed in any type of Computer.

The CNN model training was done with different conditions like the number of epochs, the dataset size, the number of convolutional layers, and image shuffling, etc. to increase the accuracy. Figure 3 depicts the CNN model accuracy comparison done using the different conditions. An average accuracy of 99.97% is obtained. A trained CNN model is used to predict a specific gesture. The identified gesture code is then sent to the central controller via Bluetooth and the controller further passes to the respective device to be switched on or switched off.

No. of Epoch	Dataset Images	Convolutional Layers	Accuracy
2	train 600, test 30	2	93.33%
2	train 6600, test 3000	2	99.67%
2	train 600, test 30	3	90.0%
2	train 6600, test 3000	3	99.97%
10	train 6600, test 3000	2	99.6%
10	train 6600, test 3000	3	99.5%
10	train 6600, test 3000	3	99.93%
20	train 6600, test 3000	3	99.63%
30	train 6600, test 3000	3	99.87%
50	train 6600, test 3000	3	99.90%
50	train 6600, test 3000	3	99.60%
100	train 6600, test 3000	3	99.73%

Figure 3: CNN Model Accuracy Comparison

CONCLUSION

This paper discusses an approach that can detect slight gestures of immobile or bedridden patients and control smart home devices using gestures. Also, the gesture recognition mechanism ensures very slight gestures are also captured and communicated through the system properly. This approach requires a CCTV camera to be installed in the patient’s room where the smart home devices need to be controlled. In this solution we present a trained CNN model, giving promising results for hand gesture recognition and prediction. This will be effectively used in real-time patient monitoring. Here the IoT device implemented correctly redirects the gestures done by the patient to the specific smart device. According to the gesture given by the patient the switch of the electric device will be turned on or switch off. The CNN model gives us more than 99.97% of test accuracy. and the IoT device is working properly with the tested smart appliances. The gesture is given to the central controller, which is capable of further processing, the controller processes the transferred gesture data and passes this to the IoT device. Then the switch of the electric device like fan, light & A/C will be switch on or switch off according to the given gesture.

To acquire a wider range of users, we plan to combine an Eyeblink gesture recognition system with the proposed solution in the future. The eye blink gesture recognition system enables the smart devices to be controlled even with a specific eye blink sequence. Eyes are to be detected and the eye blinks are to be recorded and compared with the learning model.

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