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Implementation of Human Gesture Recognition Using CNN

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Abstract

Popularity of gesture system based entirely on convolutional neural networks (CNNs). Preprocessing techniques include segmentation, polygonal approximation, contour construction, morphological filters, and resource characteristic extraction. Various CNNs are employed for training and testing, with results compared to existing architectures and protocols. All generated measurements and convergence graphs produced at any point during education are examined and contested to verify the reliability of the approach offered. Our project was created to record hand gestures as we entered and predicted textual signal languages. It makes use of the Raspberry Pi module, which is among the best for editing photos and filming videos.

Keywords: Raspberry Pi, hand gesture, feature extraction, Python, OpenCV

INTRODUCTION

The development of technology has ushered in transformative opportunities to enhance the lives of individuals facing various challenges, including hearing and speech impairment. Among the innovative solutions emerging in this domain, hand gesture recognition systems are a promising avenue. Specifically created for people with speech and hearing impairments, this system uses cutting-edge technology, especially computer vision and machine learning, to facilitate efficient communication.

Traditional modes of communication may pose limitations to people with hearing and speech impairments. Hand-gesture recognition systems seek to bridge this gap by harnessing the expressive potential of hand gestures. Through the integration of sophisticated algorithms and sensors, this system interprets and translates hand movements into meaningful interactions, thereby providing a novel means of communication for those who rely on visual cues.

In this context, the hand gesture recognition system not only represents technological innovation but also embodies a commitment to inclusivity and accessibility. By understanding and interpreting hand gestures, the system empowers individuals with hearing and speech impairments to express themselves more freely and to engage with the world in a manner that aligns with their unique communication needs. This introduction sets the stage for exploring the intricacies and benefits of the hand-gesture recognition system, highlighting its potential to revolutionize communication for individuals facing hearing and speech challenges. Machine learning has brought about a paradigm shift in how humans perceive and comprehend the world, leading to a multidimensional increase in applications. Supervised, unsupervised, and

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reinforcement learning, collectively encompassed in machine learning, have revolutionized various aspects of contemporary life and business operations. Among its applications, computer vision stands out as a field that has attracted significant scientific interest, leveraging technological breakthroughs for the betterment of humanity. Hand gestures with alphabetic indications are shown in Figure 1.

Figure 1. Hand Gesture.

A crucial societal need is addressed through the integration of computer vision into the daily activities of deaf and sign-language users. By enabling devices to identify hand gestures, computer vision facilitates communication among individuals using sign language. This study explored the creation of a powerful system capable of predicting words using hand signals. The meaning of each symbol is conveyed through hand signs, allowing users to express their desires. The system enhances the user experience by offering choices for customization, making it more comfortable and precise for achieving specific goals [9].

The proposed technique uses a convolutional neural network (CNN) for sign detection. By identifying particular features, this model compares newly created photos with the training datasets and extracts features through their layers.

This approach ensures excellent and intelligent gesture recognition for hand signals, enables programming characters, and suggests plot ideas with precision. The integration of computer vision in this context exemplifies its potential to significantly impact communication and accessibility.

Continuous studies and developments in computer vision have followed breakthroughs in machine vision technology, as highlighted in the vision [1]. Researchers have employed various strategies such as static photo categories to advance the capabilities of computer vision [2]. This technological advancement extends beyond visual categorization and finds applications in medical sensing and diagnostics [3].

LITERATURE SURVEY

Table 1 provides a brief overview of the literature on the systems suggested by several writers.

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Table 1. Literature review.

Paper name and year	System proposed	Advantages/remark
Real-time hand gesture recognition for improved communication with deaf and hard-of-hearing individuals. International Journal of Intelligent Systems and Applications in Engineering. May 2023 [1]	Real-time hand gesture recognition Using Convolutional Neural Networks (CNN).	A hand gesture recognition system has the potential to drastically alter how people with hearing impairments and those in other relevant disciplines communicate.
Comparative Study for vision-based and data-based hand gesture recognition technique. IEEE, 2017 [2]	In this paper, a comparison is made between the vision-based technique and the data glove-based technique.	In comparison to vision-based techniques, flex sensor-based techniques are less accurate (if the lighting is good; otherwise, flex-based system delivers superior accuracy).
Creation of image segmentation classifiers for sign language processing for deaf and dumb. IEEE, 2020 [3]	The hand in the raw image is identified, and segmentation is performed using Otsu's technique, which provided the static gesture recognizer with this section of the image.	When altering finger movement, this system processes information more quickly. The algorithm may, however, be unable to accurately identify wrist movement and other noteworthy characteristics that are critical to the overall quality analysis.
Hand sign recognition-based communication system for speech disabled people. IEEE, 2018 [4]	In this paper, a smart hand sign interpretation system using a smart glove is proposed to reduce the communication gap between speech-impaired people and normal people.	It satisfies real-time requirements and has a high recognition accuracy rate. With minor modifications, this technology can be employed in a variety of applications, such as the gaming industry and robotic arm control.
Different model for hand gesture recognition with a novel line feature extraction. IEEE, 2019 [5]	Seven 2D and 3D motions with different mobile cameras, backgrounds, illumination, the position of the hand, and the shape of the hand are recorded within short distances. Experiments were performed to compare the performance of training and testing in the CNN method.	With just one hand and a 98% accuracy rate, ANN has been trained to identify numbers from 1 to 10 in Kurdish Sign Language (KurdSL) using one line (fifty features) taken from black-and-white processed photos.
Hand gesture recognition using deep learning. IEEE, 2017 [6]	In this paper, a technique that commands computers using six static and eight dynamic hand gestures was proposed. The three main steps are hand shape recognition, tracing of the detected hand (if dynamic), and converting the data into the required command.	By omitting skin color segmentation, blob identification, skin area cropping, and centroid extraction for unidirectional dynamic motions, the approach was strengthened. With an accuracy of 93.09%, the prototype was successfully tested on seven different volunteers in varying lighting and background situations.
Hand gesture recognition using a convolutional neural network for people who have experienced a stroke. IEEE, 2019 [7]	Seven 2-D and 3-D motions with different mobile cameras, backgrounds, illumination, the position of the hand, and the shape of the hand are recorded within short distances. Experiments were performed to compare the performance of training and testing in the CNN method.	The developed method has 99% testing accuracy using CNN and is an effective technique in extracting distinct features and classifying data.
Aggregate features in multisample classification problems. IEEE, 2015 [8]	This paper evaluated the classification of multisample problems, such as electromyographic (EMG) data, by making aggregate features available to a per-sample classifier.	For this situation, the accuracy of this strategy is higher than that of conventional methods like the majority vote.

Sensor fusion of leap motion controller and flex sensors using Kalman filter for human finger tracking. IEEE, 2018 [10]	A novel method for tracking the fingertips of the human hand using two distinct sensors and combining their data by sensor fusion technique	The accuracy of tracking is improved in occluded cases.
Cooperative sensing and wearable computing for sequential hand gesture recognition. IEEE, 2018 [11]	A sequential hand gesture recognition system capable of detecting individuals' static and dynamic hand gestures by applying the deep learning method LSTM to classify these gestures was designed.	The suggested method performed exceptionally well in categorization, according to the experimental data. Results have positive implications for the state of HCI research and sequential hand gesture recognition.
Egocentric hand track and object-based human action recognition. IEEE, 2019 [12]	In this paper, a study regarding the usefulness of hand and object sequences for human action recognition was performed.	The results show that by only a small portion of the input, it is possible to infer a set of hand-based human motions with accuracy that is comparable to that of video-based approaches.

In an investigation [11] using an integrated SVM classifier, the authors successfully designed and implemented a cutting-edge wearable hand device as a sign-interpretation system. To illustrate the usage of the proposed smart wearable device with a text-to-speech service, an Android-based mobile application was created. Regarding comfort, adaptability, and portability, participants rated the suggested smart wearable sign interpretation system highly. The device holders do not need to be custom-made because they can accommodate a variety of hand and finger sizes owing to their 3D printing technology and flexible filaments. Future work on the proposed smart wearable hand device will consider the design of a smaller printed circuit board, the inclusion of words and sentences at the sign language level, and instantly audible voice output components.

Wu and Sun [12] suggested a wearable real-time system for recognizing American sign language in their paper. This is the first study of a system for recognizing American sign language that combines complementary signals from sEMG and the IMU JBHI-00032-2016 10 sensors. Four popular classification algorithms were investigated for our system design, and feature selection was performed to select the best subset of features from a large number of well-established features. The system was tested using 80 ASL signs that are commonly used in everyday conversations, and an average accuracy of 96.16% was achieved with 40 selected features. The importance of sEMG in the sign language task was explored.

In a study [13], the goal of the project was to produce a low-cost interface device that allows users to interact with virtual world items through hand gestures. The device uses computer vision algorithms and gesture recognition techniques to implement an application. The prototype design of the application consisted of a central computing module that tracked hand gestures using the camshift approach. To find hand positions and classify gestures, a creditworthy classifier that uses the Haar-like technique was used. Mapping the number of hand faults that arise with designated movements has been used to pattern gestures for identification. The OpenGL library was used to create virtual objects. This hand-gesture recognition technique aims to substitute the use of a mouse for interaction with virtual objects. This will be useful in promoting control applications such as virtual games and browsing images in virtual environments using hand gestures.

In a study [14], a hand-tracking-based virtual mouse application was developed and implemented using a webcam. The system was implemented in a MATLAB environment using the MATLAB Image Processing Toolbox. The outcome demonstrates that we can utilize this technology to interface with computers by gesturing with our hands rather than a mouse. The mouse function to move the cursor and click the mouse can be replaced by the system, which can also detect and track hand movements. In general, the system can recognize and follow hand movements to use them as a real-time user interface.

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Madhuri et al. [15] presented a report on a mobile Vision-Based Sign Language Translation Device for automatic translation of Indian sign language into speech in English to assist hearing and/or speech-impaired people in communicating with hearing people. It could be used as a translator for people who do not understand sign language, avoiding the intervention of an intermediate person and allowing communication using their natural way of speaking. The interactive application program for this suggested system was created using the LABVIEW software and integrated into a mobile phone. The built-in camera of the mobile phone is used to capture the images of the sign language gestures, and the operating system handles vision analysis tasks and outputs speech through the integrated audio device, reducing the need for and cost of additional hardware. Owing to parallel processing, there is very little lag time between sign language and translation. This enables nearly immediate translation identification from hand and finger movements. This can identify one-handed sign representations of the digits 0–9 and the alphabets A–Z. It is discovered that the results exhibit a high degree of accuracy and precision along with reproducibility and consistency.

PROPOSED SYSTEM

Deaf people typically communicate with hearing people who do not know sign language using one of two standard methods: authoring texts or utilizing translators. Deaf people lose their independence and privacy as a result of interpreters, who are quite expensive for everyday conversations. Text writing is ineffective as a means of communication because it is too sluggish compared to spoken or sign language, and it loses the facial expressions used while speaking or signing. Therefore, more effective and affordable means of facilitating communication between hearing and deaf individuals are required.

This section defines the hand movement processing and records the classification strategies employed in this study, as shown in Figure 2. Record extraction is a necessary step in classifier training. Furthermore, it is crucial to obtain the most information possible from areas of interest while using hand gestures.

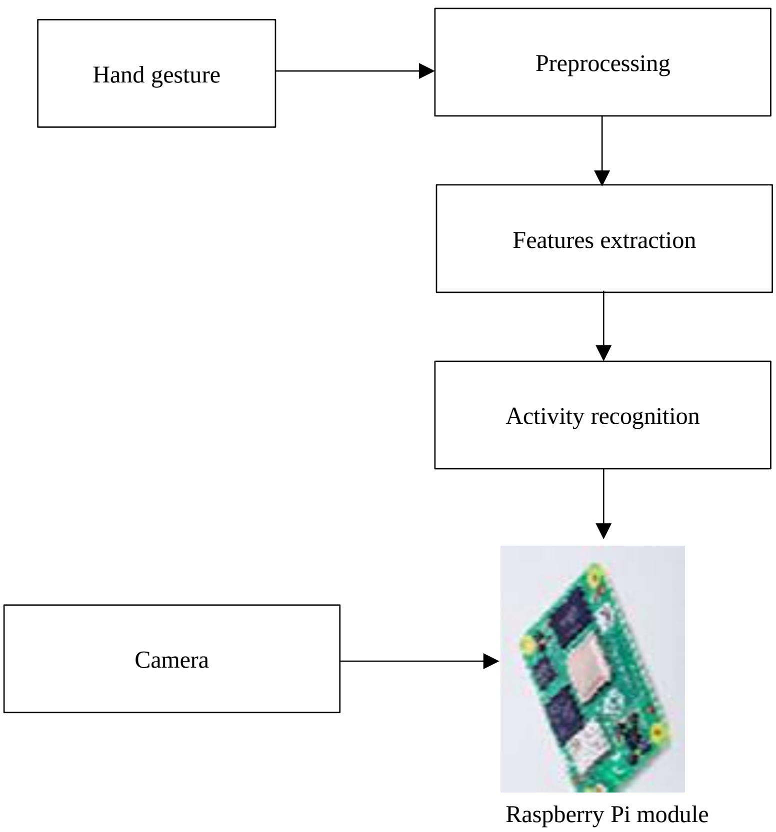

Figure 2. Proposed architecture.

The relevant information is transferred to a chosen application through the application of segmentation algorithms, filters, and morphological techniques. Extracting function vectors from hand motions is not always necessary when utilizing CNNs. Networks due to the fact the center of this form of community is the gestures themselves. Keeping those factors in mind, an excellent preprocessing section must accurately separate relevant gesture functions from legacy noise. Many ranges of accuracy loss are present in American sign languages, which are probably represented by providing sign rubdowns in the A, B, C, D, W, X, and Y formats in addition to the available training data. It could be possible to build the neural network, and it will take a while to train the algorithm. Our recommended solution has the following characteristics and is mostly based on Raspberry Pi modules: Users can record and take high-definition images and videos with the Raspberry Pi's dedicated virtual input connection. With Python and specialized Pi libraries, users may create programs that take pictures and videos and analyze them instantly.

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Frame Capturing

Data input options include body or film collection acquired using the Raspberry Pi digital camera module and transmitted to the user's hand. A 5MP digital camera module, capable of recording 1080p video and still images, as well as 720p60 and 640*480p60/dozen, was used to capture pictures of the body. The digital camera sensor has a 5-megapixel native resolution to provide an idea. Up to 1080p resolution photos can be recorded at 30 frames per second and two frames per second in the video mode. Pi's digital module can now seize at 80 frames per second in sync with the second owing to the updated firmware. The digital digicam module is perfect for mobile applications because of its small size and lightweight. Using the Raspberry Pi digital module, high-speed images at 90 frames per second (fps) are obtained. Some

- Taking pictures while filming
- Multiple resolution recordings
- Recording motion vector data
- Unencoded image capture (RGB format)
- Quick collection and handling
- Quick recording and broadcasting

MATERIALS AND METHODS

A set of video frames or a body obtained through the use of a Raspberry Pi digital digicam module oriented towards the user's hand can be utilized as input data. A 5MP digital digicam module that can record 1080p video and still photos, in addition to 720p60 and 640×480p60/ninety, is used to take pictures of the body. The digital digicam's sensor has a 5-megapixel local decision when it is in the nevertheless seizing mode. It can record videos up to 1080p at 30 frames per second in the second video mode. Pi's digital digicam module may now seize at 80 frames per second according to 2nd thanks to the updated firmware. The digital digicam module is ideal for mobile work because it is far away.

Morphological Operations

Morphological filters are often used to extract gesture additions inside the contour and portrayal of shapes. These filters are used to suppress noise and/or seal gaps to highlight or postpone the characteristics from segmentation at a certain point in hand movement detection. Erosion and dilation are the fundamental processes that characterize them; the beginning and ending are also crucial processes. Even when the same amount of clearing is used, a variety of methods address structural variables that have the broadest range of shapes, thereby producing unique final products. Two examples of structural factors are a vector and a rectangular matrix. Rectangular parts and traces may disappear from the image if an erosion approach is applied. On the other hand, the closure process fills gaps. There were a few omissions.

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Artificial Neural Network

ANNs, or artificial neural networks, are a popular classification structure. By activating artificial neurons inside the entry layer, the community is given an object to be categorized in this way. After processing these activations within the internal layers, the output layer provides the ultimate result as a sample. A single-layer community called a simple perceptron, is best suited for handling linearly separable issues. Applying a multilayer perceptron (MLP) neural community is crucial when handling non-linearly separable circumstances. The MLP is composed of an enter layer, hidden layers, and an output layer, as shown in Figure 3.

The weights of a neural network determine whether they are suitable for classification tasks. Artificial synapses are trained with weights adjusted to a particular task during the neural network training. To adjust the neural network to solve this problem, the back-propagation technique modifies the connection weights in the inner layers as the error propagates in the opposite direction. One of the most popular methods for MLP training is this method.

CNN

The CNN (convolutional neural network) that we use in our project receives hand landmarks as input as shown in Figure 4. The camera recognizes landmarks on the hand and fingers and records the video of a moving hand. After identifying the hand landmarks, the dataset was preprocessed, and feature extraction was performed. Preprocessing is performed on the hand landmarks to eliminate the background and denoise them. The user's hand, or region of interest (ROI), is isolated and recognized from the entire landmark detection process. It calculates the angle between the fingers and recognizes the landmarks of the hands and fingers. The classifier receives the computed fingertip coordinates. A convolutional neural network (CNN) recognizes the text and categories of several hand landmarks. The classifier compares the coordinates supplied to the hand landmarks and interprets the hand movements. If the hand movement is fast, then it does not detect the text; otherwise, it detects the correct text that we assign to the classifier for training. Actions such as checking, the ward are performed based on the interpreted hand movement, which is then translated into text.

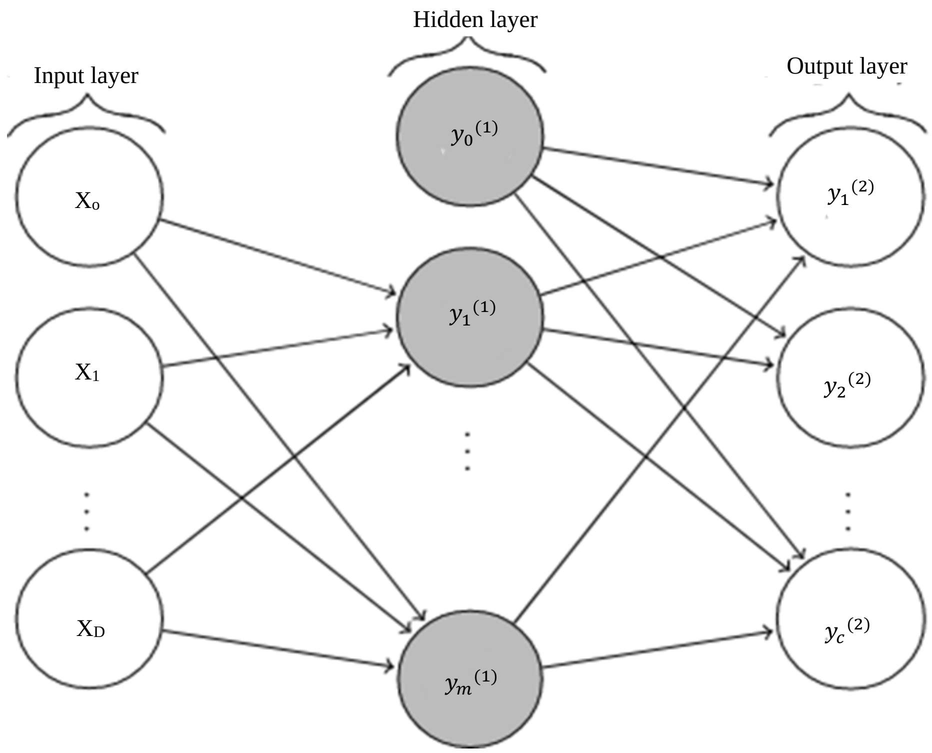

Figure 3. Connected neural network layers.

A CNN model was employed to predict hand gestures and extract the characteristics from the frames. It is a feed-forward neural network with multiple layers and is primarily used for image recognition. Each convolution layer in the CNN design comprises a pooling layer, activation function, and optional batch normalization. There are several fully connected levels. One of the photographs shrinks in size as it travels around the network. Max pooling causes this phenomenon. Class probabilities were predicted in the last layer.

Methodology

Hand Landmarks Detection

Hand landmark placement is a crucial source of information for hand gesture identification and has been effectively employed in many modern depth-map-based algorithms. This makes it possible to identify landmarks positioned inside the hand masks and at the contour.

A high-fidelity method for tracking hands and fingers involves using hand landmarks. It deduces 21 3D landmarks from a single image using machine learning (ML). Dots of different colors are used to represent tracked 3D hand landmarks; brighter dots indicate locations closer to the camera.

Hand keypoint detection is the process of identifying fingertips and finger joints in a certain image. The camera identified a hand landmark, and after using this hand landmark detection, we were able to see letters, characters, and numerals on our computer screen, as shown in Figure 5. This is the operation of the proposed system.

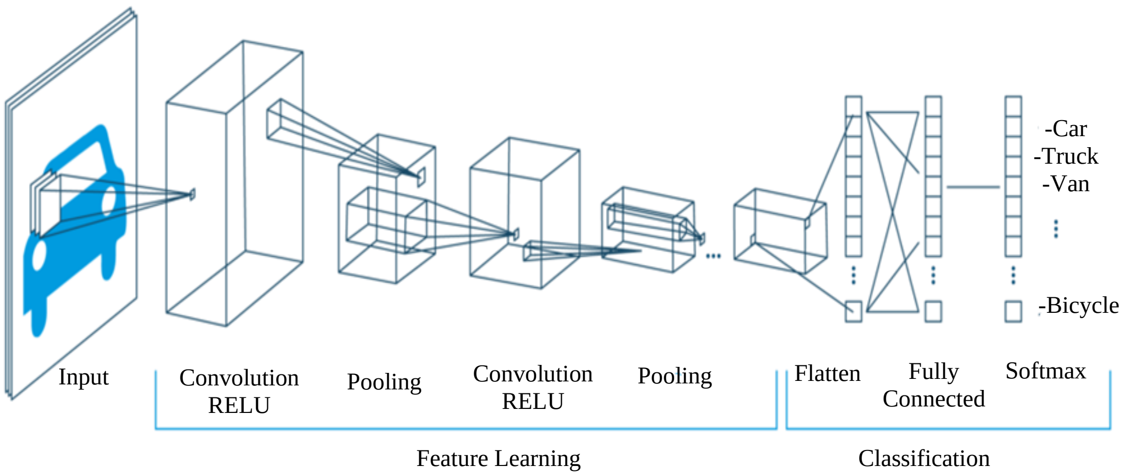

Figure 4. CNN and its layers.

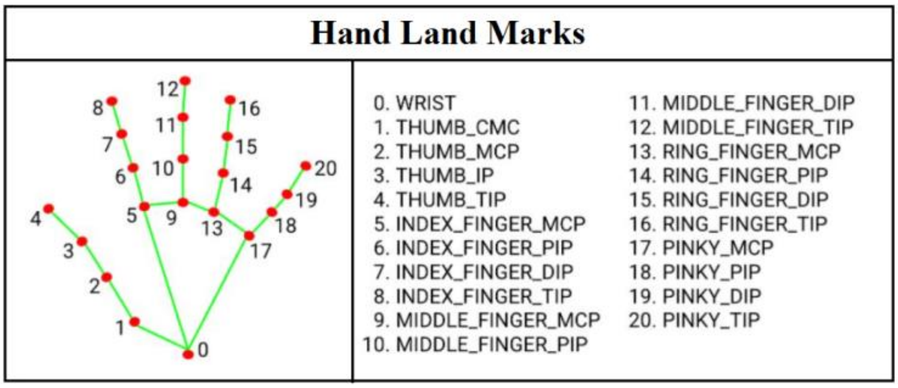

Figure 5. Hand landmarks.

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Description

1. The camera recorded the hand in motion and recognized the landmarks of the hand and fingers.
2. Hand landmarks were preprocessed to enhance their clarity and reduce noise.
3. The landmark detection method ignores the user's hand and recognizes it as the region of interest (ROI).
4. The classifier receives the computed fingertips' coordinates.
5. The classifier decodes the hand movement by comparing it with the coordinates of hand landmarks.
6. Actions such as checking the ward or anything else were translated into text or identified in the connections between hand landmarks based on the interpreted hand movement.

After determining the geodesic distance wave propagation via the fast-marching algorithm (FMA) on the images, landmark detection was performed. The inner and outer landmarks of the hand are shown in Figure 6. Without a keyboard or mouse, the user can interact with a computer.

This system offers a thorough explanation of landmark-based feature extraction. For hand gesture modeling, training, and identification, a point-based feature extraction method extracts landmarks. The point-based approach, which comprises points on the thumb, index finger, middle finger, ring finger, and little finger, is used to extract features from the hand movements. To create a range of features retrieved for training and recognition purposes, all points are merged in different ways. These points represent the geometric, angle-based, and distance properties [16, 17].

Database

To instruct CNN, we have provided ten distinct hand gestures, including:

- Fan on
- Fan off
- Thank you '
- Sorry
- Give me water
- I'm hungry
- Stop
- Bye
- Lamp on
- Lamp off

Hand gesture sets, a self-received dataset and another set found in the literature were used to categorize the findings of the investigation. Except for hand movements, the self-received dataset was entirely produced by accumulating static motions. We used a 1920 × 1080-pixel Logitech Brio camera to take pictures in a laboratory at a college with artificial lighting. We created a fringe of 400 × 400 pixels by simply removing the hand spot from the final image in our dataset.

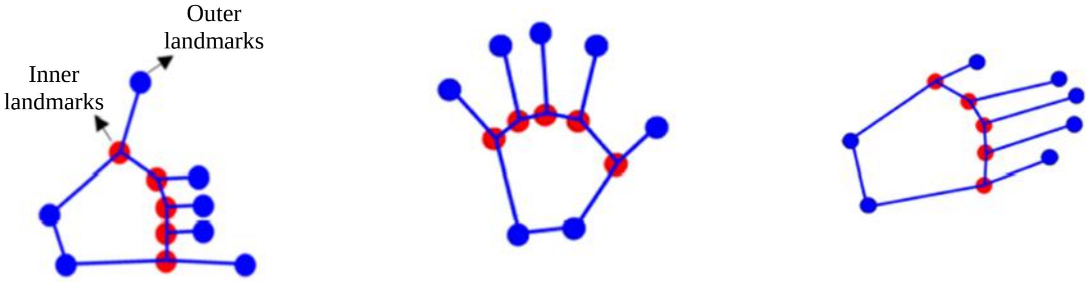

Figure 6. Inner landmarks and outer landmarks.

We applied a 20% vertical scale increase as well as 30-diploma clockwise and anticlockwise rotations to every image to diversify the dataset. As a result, there were 24 moves and a hundred samples inside the last photograph collection. It is fantastic to have a large number of samples. The hand gestures in Figure 7 display numerous variations of the gesture “FAN OFF,”

To segment skin color at the beginning of the suggested procedure, we built an MLP neural network. To achieve this, we built a network with two hidden layers, each containing ten and five neurons. The three elements in the input layer are related to the color tones in the RGB palette. One neuron in the output layer determines the binary response (0 for non-skin and 1 for skin). In our study, we trained an MLP skin classifier using five pictures. These photographs, which were employed in earlier research, demonstrate the accuracy of the proposed segmentation technique. An illustration of one of the training hand motions is shown in Figure 8.

Positive skin closures are included in the hand movement of LAMP ON, which was utilized to train the CNN and was utilized by the classifier, as shown in Figure 9.

Figure 7. Sample off-hand gesture “FAN OFF”.

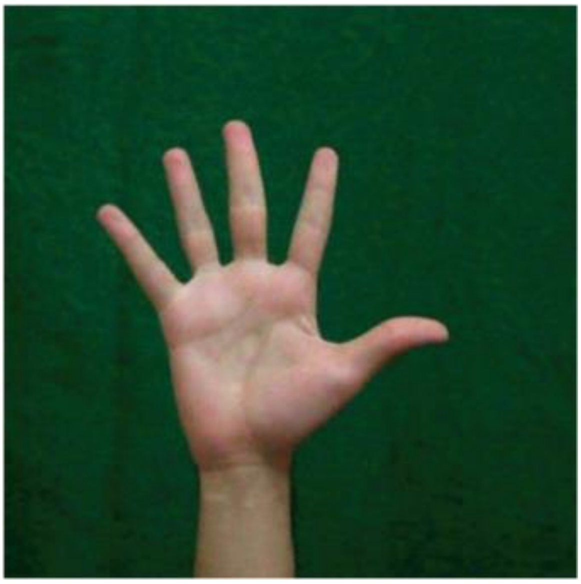

Figure 8. Sample off-hand gesture “STOP”.

Figure 9. Sample off-hand gesture “LAMP ON”.

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The “LAMP ON” sample illustrates three distinct skin types and pores, as well as which method produces the best results. As shown in Figures 10 and 11, we discovered that numerous segmentations contained holes and noise inside the hand region when segmentation education was applied to the dataset photographs. Even with the excellent results obtained from the use of morphological processes, a small number of images still exhibited noise around the edges and holes. To avoid these challenges, we developed polygonal approximation.

RESULT AND DISCUSSION

Table 2 shows a brief output of the project.

Figure 10. Hardware of the project.

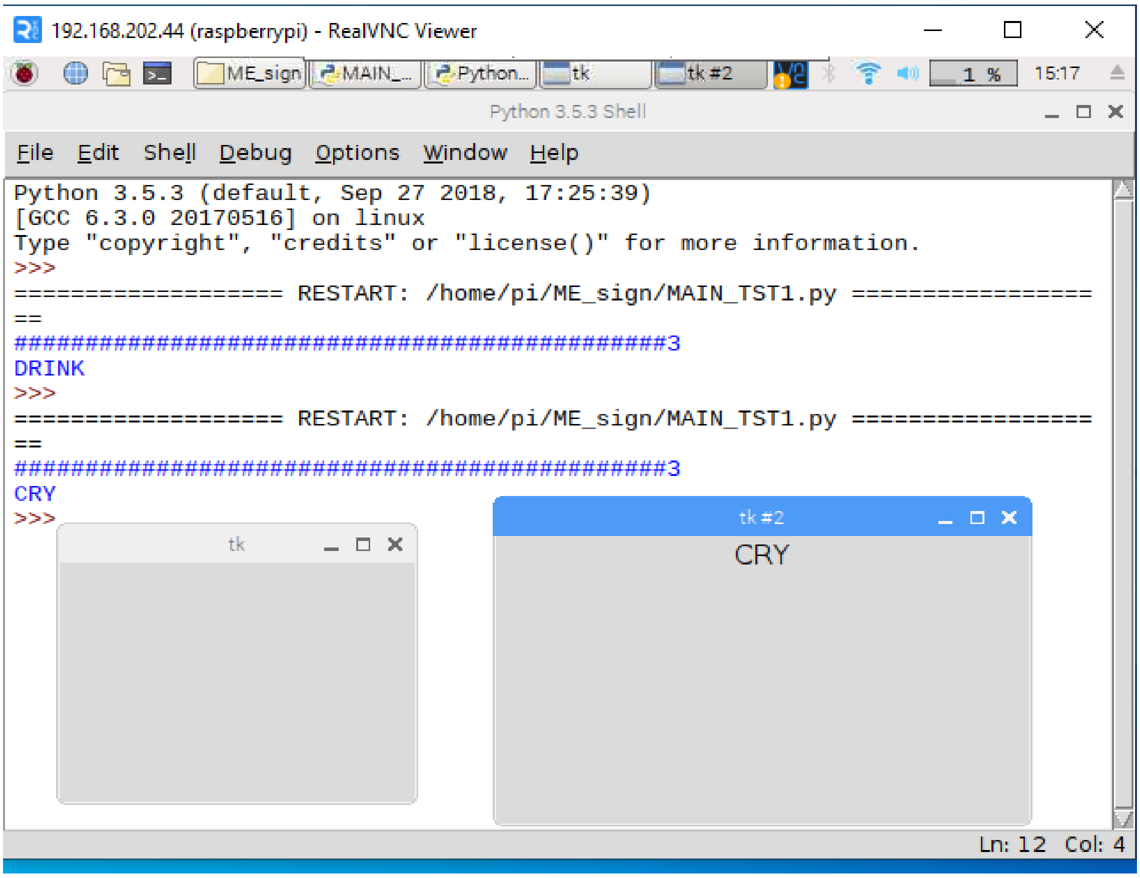

Figure 11. Output of the project.

Table 2. Output of the project.

S.N.	Hand gesture	Text symbol	Speech signal on speaker
1	CRY	tk #2 CRY	CRY
2	DRINK	tk #2 DRINK	DRINK
3	EAT	tk #2 EAT	EAT
4	JUMP	tk JUMP	JUMP
5	PICK UP	tk #2 PICKUP	PICK UP
6	PULL	tk #2 PULL	PULL
7	PUSH	tk #2 PUSH	PUSH
8	RUN	tk #2 RUN	RUN
9	SIT	tk #2 SIT	SIT
10	SLEEP	tk #2 SLEEP	SLEEP
11	STAND	tk #2 STAND	STAND
12	STOP	tk #2 STOP	STOP
13	WAKE UP	tk #2 WAKEUP	WAKE UP
14	WALK	tk #2 WALK	WALK

CONCLUSION

This study uses a CNN algorithm to generate sign language using hand landmarks. Because the CNN technique we utilized in this project is superior to other image processing and recognition algorithms, it can be used for sign language as well. Using this technique, an individual can communicate with someone who is disabled and use a computer from a distance without the need for a keyboard or mouse. Users can use hand landmarks to interact with a computer. Using CNN in this system allowed us to obtain precise results.

The conclusion of this research shows that in the COVID-19 epidemic conditions, educating deaf people is challenging. In our proposed assignment, we included 10 different hand gestures that are very useful for deaf people to learn sign languages quickly. Additionally, sign languages can be taught in textual format on computers. The ability of our project to achieve 97.91% accuracy without the help of writers or researchers is among the most amazing features.

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