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Camera-based interactive wall display using hand gesture recognition

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ABSTRACT

the recognition of Hand gestures has become a critical point as it is widely used in everyday applications. the challenge in this is to improve the recognition effect and develop a fast recognition method. Glove and led-based methods involve external devices in detecting and interpreting hand gestures, making human-computer interaction less natural. So, different approaches have been used previously that use purely hand gestures in many systems based on human-computer interaction. This system provides a more natural human-computer interaction; it must be made efficient processing speed of classifying the test data (images) from among the training data (database stored for gestures recognition). This speed makes gesture recognition more effective and reliable to use as compared to previously proposed methods. In this research paper, a proposed system based on a camera-based interactive wall display using bare hand gestures with efficient processing speed for controlling the speed of the mouse and other functions. This system has three modules: one uses Genetic Algorithm and Otsu thresholding to identify the query images as the right or wrong gesture and perform the correct action in case of the proper motion, another module controls functions outside of PowerPoint files or Word documents, e.g., to open folders and go through drives, and the third module uses the convexity hull method for finding the number of fingers open in the user's gesture and operates accordingly.

1. Introduction

A range of remarkable developments in the field of hand gesture recognition technology has been seen in recent years (Damaneh et al., 2023). This technology has revolutionized human-computer interaction, allowing users to operate computer systems through intuitive and natural hand gestures. Hand gesture recognition involves several processes, which include image capture, hand detection, hand extraction, and gesture classification (Wu et al., 2023; Fayyaz et al., 2023). These processes have become increasingly easy to use, enabling users to interact easily with computers and other devices. There are various methods for hand gesture recognition, including glove and led-based methods (Lin et al., 2022; Singh & Chaturvedi, 2022). However, these methods require external devices that could interfere with the naturalness of the human-computer interaction (Bi et al., 2023). As a result, researchers have developed techniques that merely use hand gestures to control computer functions, enabling more natural interaction between users and computer systems (Jiang et al., 2023). Hand gesture recognition technology has numerous practical applications in various fields, including gaming, virtual reality, healthcare, and education (Maskeliūnas et al., 2023). For instance, in healthcare, this technology can control medical equipment through hand gestures, allowing surgeons to operate without physical contact, thus reducing the risk of infections. With the use of cutting-edge technology in education, interactive teaching aids can be created using hand gesture recognition technology, increasing learning effectiveness and engagement. (Dimitriadou & Lanitis, 2023). However, the accurate detection and extraction of the hand from an image or video feed remain one of the primary challenges of hand gesture recognition (Sharif et al., 2022; Cohen et al., 2022). This requires sophisticated algorithms to identify the hand based on shape, color, and movement (Alyami et al., 2023). Machine learning algorithms often classify hand gestures based on a predefined set of gestures. The advances in deep learning algorithms and the availability of large datasets have significantly contributed to the advancement of gesture

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recognition technology (Ghosh et al., 2021). These advancements have made the technology more accessible and user-friendly, enabling users to interact with computers and other devices more naturally and intuitively (Morajkar et al., 2023; Islam Chowdhury et al., 2020). This research aims to enhance human-computer interaction further. This system projects the system's screen image onto a wall and is used as a computing platform to support gesture interaction between humans and computers. This system can make presentations more accessible by hand gestures interacting with the display wall. The mouse cursor is also controlled, and various operations can be performed by hand gestures in front of the camera. It increases users' interest and convenience. Section 2 of this research paper includes an analysis of related prior work on human-computer interaction. Section 3 outlines the suggested approach. The experimental results of various hand gestures of a system and their rates of recognition are displayed in Section 4. Section 5 gives a conclusion and describes how the current approach is appropriate and easy to use compared to previous methods.

The proposed novelty of this paper is a camera-based interactive wall display system that uses bare hand gestures for human-computer interaction without requiring external devices. The system is designed to have efficient processing speed for classifying test data (images) from among the training data stored in a database for gesture recognition, making gesture recognition more effective and reliable than previously proposed methods. The system comprises three modules, including one that uses Genetic Algorithms and Otsu thresholding for identifying the query images as the right or wrong gesture and performing the correct action, another module that controls functions outside of PowerPoint files or Word documents, and the third module that uses the convexity hull method to find the number of fingers open in the user's gesture and operate accordingly.

2. Related work

There are numerous hand gesture recognition techniques have been proposed and implemented before. Viola Jones method (Yun & Peng, 2009) is a well-known technique for hand gesture detection. This method can accurately detect hand regions by locating them with a blue rectangle. For feature extraction, it incorporates a set of Haar-like features into the image representation. Xu et al. (2009) presented a method that uses a vision-based hand-tracking approach. This approach is mainly used for Hand gesture segmentation. A self-organizing map (SOM) is another technique, for hand gesture recognition using 5DT data gloves, proposed by Jin et al. (2011). This technique is a machine learning algorithm in which raw data is used as input vectors and then plots a mapping between this data and gesture commands. A camera-based handwriting gesture recognition system is used for hand-held devices like mobile phones. Edge detection is implemented for each frame and edge histograms are plotted. The method proposed by Gu et al. (2012) has two modules, one for enhanced TSL self-adaptive hand area detection and the other for contour signature-based finger detection. It uses employs the contour signature technique. In this technique, the distance sequence from contour points and moment determines fingertip points. Using a threshold box in HSV color space, the hand area is roughly segmented. Bainbridge and Paradiso (2011) proposed a wearable hand gesture recognition system that detects hand gestures. RFID (radio frequency electromagnetic fields) is used to detect hand gestures. Tags or sensors are attached to the fingers and are identified using the electromagnetic field. Panwar (2012) proposed another technique in which the hand is detected through shape parameters. K-means clustering is used to extract hand from the image. Trindade et al. (2012) proposed a technique in which color and to detect hand gestures depth images are used. The hand region is filtered out using a color filter. The sensor is used on the palm that detects hand pose. The hand's center is formulated using the k-means algorithm. Hand gesture is detected using a depth histogram. Modler & Myatt (2008) propose a method in which sound and music are controlled using hand gestures. The proposed system uses left-hand gestures for music control. It mainly helps to differentiate between different gestures for instance pointing left, pointing right, shaking hand, moving up and down, etc. Lin et al. (2012) propose a method for hand gestures. First, the hand is tracked using a skin model that uses color information. A single Gaussian model differentiates between skin colors and the hand region gets identified. Hand gestures are detected using saliency point detection. Two points such as edge points and inner points get detected using this method. Zhou et al. (2016), proposed a system that can abstract the gesture of the extensional finger and fluxional finger with high accuracy. The proposed algorithm takes no effect on the results by hand rotation and finger angle variation Lahiani and Neji (2018) presented an investigation for improving hand gesture detection, particularly for mobile devices. They presented a technique for static hand gesture recognition for the mobile system. In this system, they combined the histogram of oriented gradients (HOG) and (LBP). The combined feature achieved a detection rate of 92% accuracy. Shanthakumar et al. (Barbhuiya et al., 2021) proposed a novel angular velocity model. The model works in real-time capturing the 3D motion data through the sensor-based system. The proposed model captures both static and dynamic data in real-time for hand gesture recognition. Calado et al. (2022) presented a model which is based on geometric approaches. This method supports visualization and geometrical interpretation for gesture recognition.

Baumgartl et al. (2021) proposed a technique to detect simple hand gestures which are used in a variety of. the technique was based on a convolutional neural network on MobileNetV2. The combination produced an accuracy of 99.69% in detecting the hand gesture precisely. Alnuaim et al. (2022) presented a model to detect hand gestures used in sign language. The system was composed of two convolutional neural network models and both were trained separately on the dataset of Arabic sign language. The final results of both models were combined to achieve more accurate results. the hand gesture images were first processed and then fed into the models which were ResNet50 and MobileNetV2. The models achieved an accuracy of 97%. Xu et al. (2022) presented a technique to detect hand gestures when it is static or dynamic, for the static hand gesture detection recognition the palm is detected by contouring the hand gesture image and applying the Distance Transform Algorithm. For the localization of finger K- The curvature-Convex Defect Detection algorithm was used. A recognition algorithm was presented for static gesture recognition, and for dynamic hand gesture recognition Improved Dynamic Time Warping algorithm was used. Chua et al. (2022) presented a system that uses object detection techniques combined with handcrafted rules for recognizing dynamic hand gestures on a computer. The system was based on the YoloV3 and RGB cameras for the localization and recognition of hand gestures. A self-designed database was used and it achieved an accuracy of 96.68%. Azim et al. (2023) presented a tool for the recognition of foot gestures when hands are unavailable. The tool can produce a gesture set that helps produce the data set of foot gestures. It works by dividing the gesture into atomic actions. The tool gives a very low false positive, tested on nine datasets of gesture designers. the use of intelligent systems is very common these days for the detection and segmentation of objects within the image Calisto et al. (2022). Intelligent agents are fast and have been very successful with high true prediction rates. Vatavu (2023) introduces a taxonomy for index- Finger Augmentation Devices (iFAD). It was tested on a dataset composed of 6369 gestures gathered from 20 participants. It has been seen in the results that the iFAD is very fast obtaining an average of 1.84 s. The study showed that the iFAD gestures are twice faster as compared to the other gestures produces by the body parts. The hand gesture could be found by the techniques used to detect the objects with assertive and non-assertive tones also, as used by Calisto et al. (2023). The researcher used it for the detection of tumors and the method received promising results. Kumar and Pandian (2023) used the Convolutional Deep VGG-16 (CDVGG-16) for the recognition of sign language which uses hand gestures to produce sign.

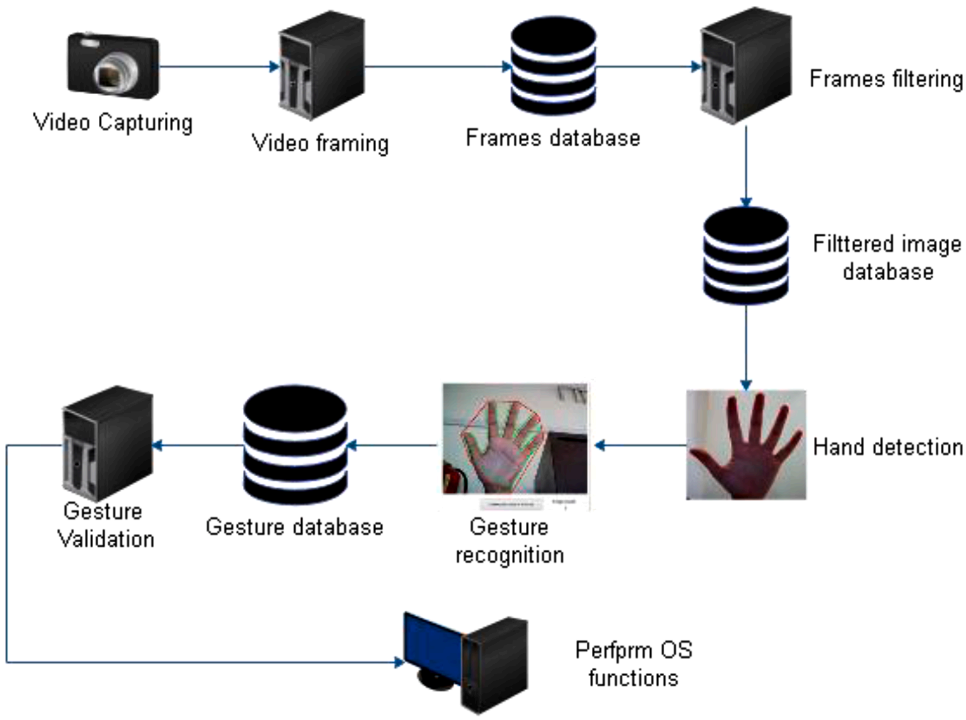

Fig. 1. System architecture.

The blocks used in the system were composed of 2D Convolution and Max pooling Layers. For the feature extraction VGG-16 was used. The Sign Language model (SLR) was introduced with CDVGG-16 classifier. The proposed framework produced an accuracy of 95.6% accuracy.

Most of these techniques used hardware-based systems for hand gesture recognition. this makes human-computer interaction difficult and uneasy. Also in poor light conditions, hand areas were not detected correctly. Most of the applications have not used user-friendly interfaces and needed training to use the application. In this article, a method has been proposed that overcomes these difficulties to some extent and enables the user to use hardware-free hand gestures to control operations of Powerpoint files, and Word documents and to control mouse cursor functions more naturally and interactively. Also, the user has to just start the application and control systems operations through hand gestures. The user does not need training for the proper operation of the application.

2.1. Research problem

This research makes use of AI and Image processing techniques to enable the users to control the cursor on the computer screen for browsing the files and folders and performing left and right-click operations with the index finger. To operate PowerPoint presentations with specified gesture movements and scroll pdf documents up and down with separate types of gestures. And Genetic algorithm helps to build a speedy way of classifying the test data (images) from among the training data (database stored for gestures recognition).

3. Proposed methodology

The methodology proposed by a given system is shown by the system architecture in the following Fig. 1.

Hand gestures are captured and recorded as single frames. These frames are passed for preprocessing like smoothing and resizing. The hand detection module is then given the input image. Then hand extraction is performed for cropping the hand region from the image. Now the image is ready for gesture validation. If the gesture of the test image matches with any of the dataset images, then the corresponding OS operation is performed. Binary images are used as dataset images as well as test frames. All the processing is performed on binary images. The size of real-time captured frames is maintained according to the dataset images. The camera used for the system is compliant with USB 2.0 Interface, Compatible with MS Windows XP Service Pack 3, Auto-focus system, Up to 2-megapixel resolution, Color depth: 24-bit true color or above, Video capture: Up to 1600 × 1200 pixels (HD quality). With the auto focus capability, the camera captured the sharp image focusing the object. The camera could handle the dim lightning as well as bright light. However dim lightning could introduce noice and blur. Bright light is best if it is not the sun light. In case of mix light it uses the autofocus for the best result. Two major modules of the system are Gesture Validation and Cursor Control. The steps of the gesture validation module are shown in the following flowchart in Fig. 2.

3.1. Video capturing and frames formation

A real-time capturing device like a webcam or external USB-connected camera is used for recording the video. Video is converted into frames. Each frame is captured by an interval of 2 s. Each frame is captured and processed side by side.

3.2. Frames preprocessing

Frames are preprocessed before applying recognition techniques. The frame is resized to the size of the dataset images. Filters are applied to remove noise from the image. And finally, a clear image is obtained.

3.3. Hand detection

For hand detection, firstly the contrast function is applied to enhance skin color, the skin detection algorithm is then executed. From the captured frame, skin is detected for a specific YGBR value. The system is then trained to detect lighter to darker skin colors. After skin detection, the entire portion other than the skin areas is removed from the image.

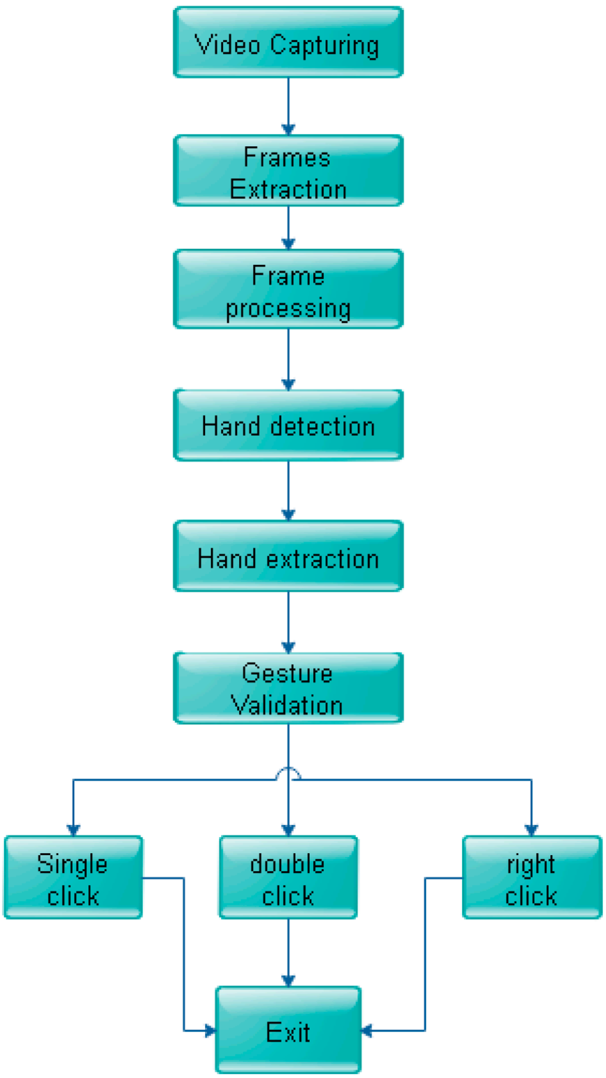

Fig. 2. Gesture validation flow chart.

Fig. 3. Video frame.

Fig. 4. Extracted hand gesture.

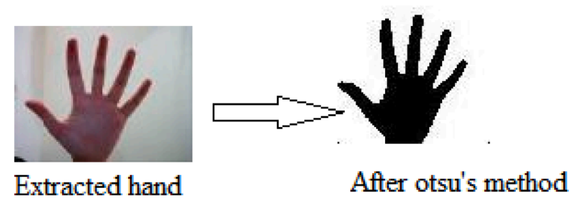

Fig. 5. Extracted hand gesture.

Fig. 6. Hand gesture dataset.

3.4. *Hand extraction*

The hand extraction is performed based on the connected component algorithm. The connected component algorithm takes the largest connect part from the image which is always the hand region. The hand region is cropped out of the image in this manner, and the rest of the image is eliminated. Now the obtained image is ready for validation (Figs. 3 and 4).

3.5. *Hand gesture validation*

Once the hand area has been extracted from the image, it is then compared with all the images present in the dataset through the Euclidean distance method. First of all user's hand image is converted into a binary image using otsu's method that helps to make the background of an image uniform as shown in Fig. 5.

All dataset images are stored in binary form. Euclidean distance among the user's hand gesture image and dataset images is found by subtracting every pixel of the user's hand image from the respective pixels of all images in the dataset. The Euclidean distance formula is shown below.

$$Euclidean = (float)(Math.Sqrt((clr - clr1) * (clr - clr1)));$$

Where clr is captured frame pixel and clr1 is the dataset image pixel.

Among all dataset images, the image that has the smallest Euclidean distance with the user's hand gesture image, will be the final match for the given hand gesture, and hence corresponding operation will be performed against that gesture e.g. scroll up, scroll down, close .ppt or . word file. For single-hand gestures, the dataset has similar gesture images from various angles to provide the best match for a real-time captured frame. Fig. 6 shows some of the samples.

3.6. *Algorithms including AI*

We used an improved Genetic Algorithm and Otsu thresholding to identify the query images as the right or wrong gesture and perform the correct action in case of the right gesture. The genetic algorithm helps to build a speedy way of classifying the test data (images) from among the training data(database stored for gesture recognition). This speed makes gesture recognition more effective and reliable to use in this research as compared to previously proposed methods.

3.7. *Genetic algorithms*

To find the best solution genetic algorithm used the technique of finding the fittest individual from the pool of the population. In the

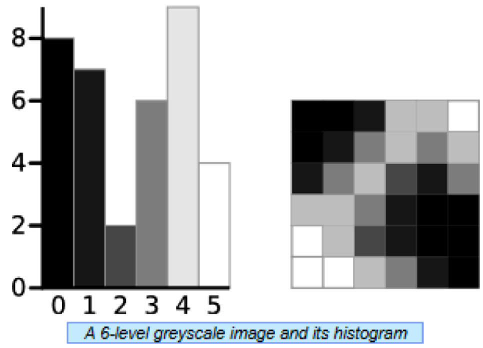

Fig. 7. A 6-level greyscale image & its histogram.

initial state, a population of the possible solution is given to the problem. The provided solutions are more refined by recombination and mutation methods as in the natural genetic process. This results in producing new children and it continues over various generations. A fitness value that is based on the objective function is given to the function. The fitter the candidate the more is the chance to pass on to the next generation.

3.8. Otsu thresholding

To calculate the measure of the spread for the pixels, the Otsu threshold method is used. This is done so pixels on either side of the threshold are measured, the foreground and background. The main aim is to find the threshold value which has a minimum spread sum of the foreground and background. A 6 × 6 image demonstration is shown below in Fig. 7.

3.9. Cursor control

The cursor control flow is shown in Fig. 8:

3.10. Fingers count approach

In this project, the mouse cursor was controlled through hand gestures to perform the click function to open folders and .ppt and .doc files. Also, the mouse cursor was moved with hand motion by finding the Center of the palm. To control mouse clicks through hand gestures, the first skin part is detected to extract the hand area from real-time video. For this purpose YCbCr filter was used that helped to get skin areas. Erosion and dilation of the image are done after skin detection. Gaussian filter is applied to filter the image. The most significant portion of the skin area is always the hand detected by finding the most prominent

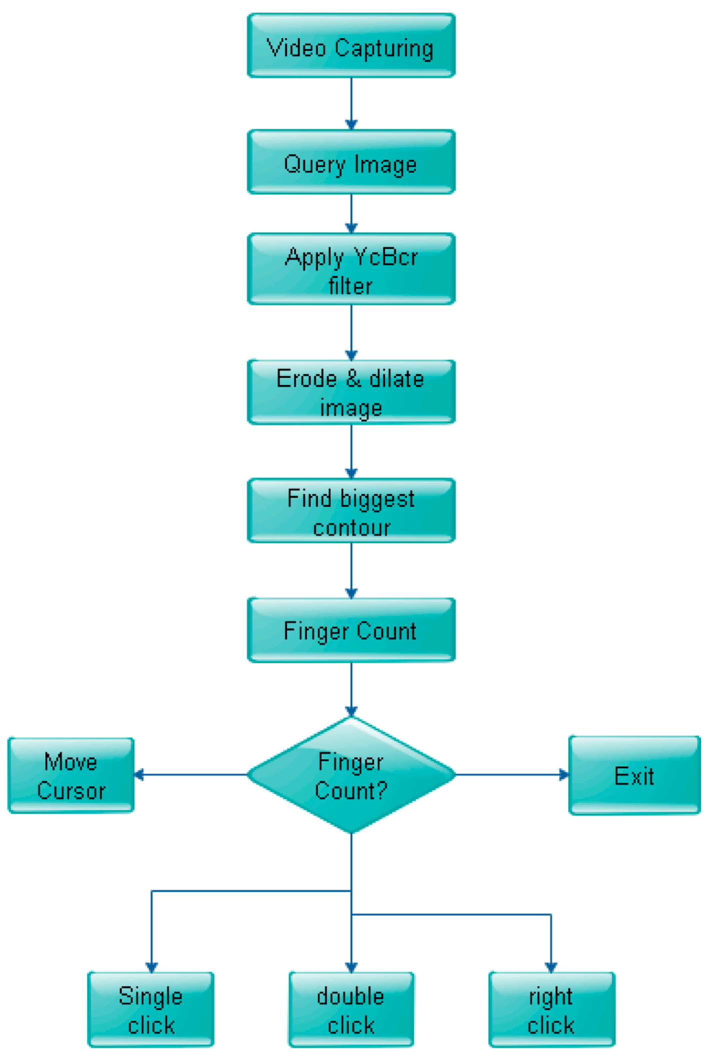

Fig. 8. Cursor control flowchart.

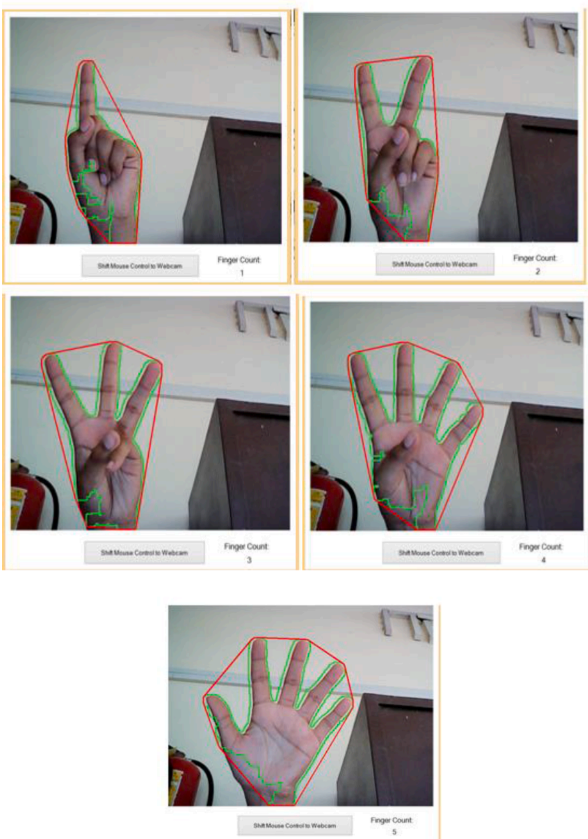

Fig. 9. Finger count.

contour. Convexity defects are used to count the number of fingers in the user's gesture image. For instance, the exit function is performed if the finger count is five. One "move cursor" function is performed when the finger count is.

Similarly, for finger count two, three, and four, a single operation of a single click, double click, and right click are performed, respectively. The Center of the palm is detected to control cursor movement. For this purpose, coordinates of the Center of the contour were found. The mouse cursor is controlled by hand by finding the contour center. In case of an invalid gesture, the cursor will not move or perform the click function. The system is capable to train on more hand gestures if new hand gestures are inserted in the system. it will work the same way as it is doing for the current gesture database. Fig. 9 shows soe images of finger counts.

4. Experimental results

A comprehensive real-time experimentation is critical for such systems as demonstrated by multiple studies I this field (Miah et al., 2023; Calisto et al., 2017; Schak & Gepperth, 2022). Therefore, a complete real-time performance of hand gestures has been evaluated in this section, and the results have been shown in Tables 1 and 2. 60 real-time images of each hand gesture have been processed and tested. Sometimes motion's required function was not performed due to invalid lightning conditions or inappropriate performance of gestures. However, the table results show that the correct performance percentage occurred between 90% and 98%, which is a suitable test result for this application. Table 1 shows hand gestures when the user's hand movement controls the cursor. The first gesture was with all fingers closed and the action mapped against it is system shut down. 56 images were validated by the system out of a total of 60. The gesture received 93.33% recognition rate. The second gesture was with index finger, opened for controlling the mouse cursor. 55 images were validated by the system from an input set of 60 images and it achieved recognition rate of 91.66%. The gesture with index and middle fingers, opened for single click produced 95% recognition rate. The gesture with index and ring fingers opened for double click achieved 96.66% recognition rate. The gesture with index, middle, ring and little fingers opened for right click achieved 91.66%. The gesture with all five fingers opened for the exit action received a recognition rate of 90%.

Table 2 shows gestures used inside currently open PowerPoint or Word documents to perform scroll up, scroll down, and close functions. The gestures overall performed well on Power Point and Word file as compared to previous for the system receiving high recognition rate for some gestures.

4.1. Average recognition rate: 93.7%

4.1.1. Overall average recognition rate: (93+93.72)/2 = 93.35%

Our proposed systems achieved a higher accuracy rate as compared to the other existing systems. Table 3 presents the comparison of existing techniques with our system.

5. Conclusion

In this study, a method has been proposed to recognize hand gestures and operate their respective functions. We used an improved Genetic Algorithm and Otsu thresholding to identify the query images as the

Table 1
Test results of hand gestures for mouse cursor control.

Gesture Name	Input images	Validated images	Recognition rate= (Input/validated)*100	Function Against Gesture
Gesture with all fingers closed	60	56	93.33	System Shut down
Gesture with index finger open	60	55	91.66	Mouse cursor control
Gesture with index and middle finger open	60	57	95	Single click
Gesture with index, middle and ring finger open	60	58	96.66	Double click
Gesture with index, middle, ring and little finger open	60	55	91.66	Right click
Gesture with all five fingers open	60	54	90	Exit

Table 2
Test results of hand gestures for functions of powerpoint and word files.

Gesture Name	Input images	Validated Images	Recognition rate (%)	Function Against Gesture
Gesture with only index and small finger open	60	59	98.33	Show slide show of PowerPoint
Gesture with all fingers closed	60	54	90	Scroll down to the next slide or page
Gesture with only thumb open	60	55	91.66	Scroll up to the previous slide or page
Gesture with all five fingers open	60	57	95	Close the currently open file or explorer window

Table 3
Comparison table.

S#	Research Paper	Recognition Rate
1.	Yun and Peng (2009)	85%
2.	Xu et al. (2009)	91%
3.	Jin et al. (2011)	91%
4.	Gu et al. (2012)	91%
5.	Lahiani and Neji (2018)	92%
6.	Given experiment	93.35%

right or wrong gesture and perform the correct action in case of the proper motion. The genetic algorithm helps build a speedy way of classifying the test data (images) from the training data (database stored for gesture recognition). This speed makes gesture recognition more effective and reliable in this research than previously proposed methods. Video of hand gestures were captured through a camera. Video frames are then preprocessed to improve the quality of structures. The contrast function was applied to the captured frames to enhance the color of skin pixels. The hand's area was extracted using skin detection and a connected component algorithm. The best match between the images from the dataset and the captured frame was determined using the Euclidean distance formula. The dataset image with the shortest distance from the captured frame is considered to be more similar and validated against the captured frame. The mouse cursor was also controlled using the finger count method. The proposed process does not involve hardware like data gloves or LED lights for hand gesture detection. The proposition provides a more natural way to communicate with computer systems. The technique performs well and takes less amount of time to validate gestures. It is also user friendly where users do not require any special training to operate it. The users just have to perform motions in front of the camera, and their respective functions will be served.

CRediT authorship contribution statement

Rida Zahra: Conceptualization, Methodology, Software. **Afifa Shehzadi:** Conceptualization, Methodology, Software. **Muhammad Imran Sharif:** Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation. **Asif Karim:** Data curation, Writing – original draft, Writing – review & editing, Supervision. **Sami Azam:** Conceptualization, Methodology, Software, Supervision. **Friso De Boer:** Validation. **Mirjam Jonkman:** Validation. **Mehwish Mehmood:** Visualization, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset of the images used can be downloaded from: https://charlesdarwinuni-my.sharepoint.com/:u:/g/personal/asif_karim_cdu_edu_au/ER9Z3CwJgr5KtMmRJ-AxRCYBbWQWeid2otisGXCrZ0qQMQ?e=zClIJ0

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References

Alnuaim, A., et al. (2022). Human-computer interaction with hand gesture recognition using ResNet and MobileNet. *Computational Intelligence and Neuroscience, 2022*.

Alyami, J., et al. (2023). Tumor localization and classification from MRI of brain using deep convolution Neural Network and Salp Swarm Algorithm. *Cognitive Computation*, 1–11.

Azim, M. A. R., Rahman, A., & Heo, S. (2023). SequenceSense: A tool for designing usable foot-based gestures using a sequence-based gesture recognizer. *International Journal of Human-Computer Studies, 176*, Article 103035.

Bainbridge, R., & Paradiso, J. A. (2011). Wireless hand gesture capture through wearable passive tag sensing. In *Proceedings of the 2011 international conference on body sensor networks*. IEEE.

Barbhuiya, A. A., Karsh, R. K., & Jain, R. (2021). CNN based feature extraction and classification for sign language. *Multimedia Tools and Applications, 80*(2), 3051–3069.

Baumgartl, H., et al. (2021). Vision-based hand gesture recognition for human-computer interaction using MobileNetV2. In *Proceedings of the 2021 IEEE 45th annual computers, software, and applications conference (COMPSAC)*. IEEE.

Bi, S., et al. (2023). Flexible pressure visualization equipment for human-computer interaction. *Materials Today Sustainability*, Article 100318.

Calado, A., et al. (2022). A geometric model-based approach to hand gesture recognition. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52*(10), 6151–6161.

Calisto, F. M., Ferreira, A., Nascimento, J. C., & Gonçalves, D. (2017). Towards touch-based medical image diagnosis annotation. In *Proceedings of the 2017 ACM international conference on interactive surfaces and spaces*. https://doi.org/10.1145/3132272.3134111

Calisto, F. M., Nunes, N., & Nascimento, J. C. (2022). Modeling adoption of intelligent agents in medical imaging. *International Journal of Human-Computer Studies, 168*, Article 102922.

Calisto, F. M., et al. (2023). Assertiveness-based agent communication for a personalized medicine on medical imaging diagnosis. In *Proceedings of the 2023 CHI conference on human factors in computing systems*.

Chua, S. D., et al. (2022). Hand gesture control for human–computer interaction with Deep Learning. *Journal of Electrical Engineering & Technology, 17*(3), 1961–1970.

Cohen, J. E., et al. (2022). Low-income and middle-income countries leading the way with tobacco control policies. *BMJ Innovations, 8*(1), 4–8.

Damaneh, M. M., Mohanna, F., & Jafari, P. (2023). Static hand gesture recognition in sign language based on convolutional neural network with feature extraction method using ORB descriptor and Gabor filter. *Expert Systems with Applications, 211*, Article 118559.

Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. *Smart Learning Environments, 10*(1), 1–26.

Fayyaz, A. M., et al. (2023). An integrated framework for COVID-19 classification based on ensembles of deep features and entropy coded GLEO feature selection. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 31*(01), 163–185.

Ghosh, P., et al. (2021). A comparative study of different deep learning model for recognition of handwriting digits. In *Proceedings of the 2020 international conference on IoT based control networks and intelligent systems (ICICNIS 2020)* (pp. 857–866). https://doi.org/10.2139/ssrn.3769231. January 192020.

Gu, L., Yuan, X., & Ikenaga, T. (2012). Hand gesture interface based on improved adaptive hand area detection and contour signature. In *Proceedings of the 2012 international symposium on intelligent signal processing and communications systems*. IEEE.

Islam Chowdhury, A., et al. (2020). An automated system in ATM booth using face encoding and emotion recognition process. In *Proceedings of the 2020 2nd international conference on image processing and machine vision*.

Jiang, L., et al. (2023). SmartRolling: A human–machine interface for wheelchair control using EEG and smart sensing techniques. *Information Processing & Management, 60*(3), Article 103262.

Jin, S., et al. (2011). SOM-based hand gesture recognition for virtual interactions. In *Proceedings of the 2011 IEEE international symposium on VR innovation*. IEEE.

Kumar, G. M., & Pandian, A. (2023). A constructive deep convolutional network model for analyzing video-to-image sequences. *Data & Knowledge Engineering, 144*, Article 102119.

Lahiani, H., & Neji, M. (2018). Hand gesture recognition method based on HOG-LBP features for mobile devices. *Procedia Computer Science, 126*, 254–263.

Lin, L., Cong, Y., & Tang, Y. (2012). Hand gesture recognition using RGB-D cues. In *Proceedings of the 2012 IEEE international conference on information and automation*. IEEE.

Lin, P., et al. (2022). LED screen-based intelligent hand gesture recognition system. *IEEE Sensors Journal, 22*(24), 24439–24448.

Maskeliūnas, R., et al. (2023). BiomacVR: A virtual reality-based system for precise human posture and motion analysis in rehabilitation exercises using depth sensors. *Electronics, 12*(2), 339.

Miah, A. S., Hasan, Md. A., & Shin, J. (2023). Dynamic hand gesture recognition using multi-branch attention based graph and general deep learning model. *IEEE Access, 11*, 4703–4716. https://doi.org/10.1109/access.2023.3235368

Modler, P., & Myatt, T. (2008). Recognition of separate hand gestures by time-delay neural networks based on multi-state spectral image patterns from cyclic hand movements. In *Proceedings of the 2008 IEEE international conference on systems, man and cybernetics*. IEEE.

Morajkar, A., et al., Hand gesture and voice-controlled mouse for physically challenged using computer vision. Advanced engineering days (AED), 2023. 6: P. 127–131.

Panwar, M. (2012). Hand gesture recognition based on shape parameters. In *Proceedings of the 2012 international conference on computing, communication and applications*. IEEE.

Schak, M., & Gepperth, A. (2022). Gesture recognition on a new multi-modal hand gesture dataset. In *Proceedings of the 11th international conference on pattern recognition applications and methods*. https://doi.org/10.5220/0010982200003122

Sharif, M. I., et al. (2022). Deep learning and kurtosis-controlled, entropy-based framework for human gait recognition using video sequences. *Electronics, 11*(3), 334.

Singh, S. K., & Chaturvedi, A. (2022). A reliable and efficient machine learning pipeline for american sign language gesture recognition using EMG sensors. *Multimedia Tools and Applications* (pp. 1–39). USA: Kluwer Academic Publishers.

Trindade, P., Lobo, J., & Barreto, J. P. (2012). Hand gesture recognition using color and depth images enhanced with hand angular pose data. In *Proceedings of the 2012 IEEE international conference on multisensor fusion and integration for intelligent systems (MFI)*. IEEE.

Vatavu, R. D. (2023). iFAD gestures: Understanding users' gesture input performance with index-finger augmentation devices. In *Proceedings of the 2023 CHI conference on human factors in computing systems*.

Wu, H., et al. (2023). Thermal image-based hand gesture recognition for worker-robot collaboration in the construction industry: A feasible study. *Advanced Engineering Informatics, 56*, Article 101939.

Xu, H., et al. (2009). Real-time hand gesture recognition system based on associative processors. In *Proceedings of the 2009 2nd IEEE international conference on computer science and information technology*. IEEE.

Xu, J., et al. (2022). Robust hand gesture recognition based on RGB-D Data for natural human–computer interaction. *IEEE Access, 10*, 54549–54562.

Yun, L., & Peng, Z. (2009). An automatic hand gesture recognition system based on Viola-Jones method and SVMs. In *Proceedings of the 2009 second international workshop on computer science and engineering*. IEEE.

Zhou, Y., Jiang, G., & Lin, Y. (2016). A novel finger and hand pose estimation technique for real-time hand gesture recognition. *Pattern Recognition, 49*, 102–114.