e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:04/April-2024 Impact Factor- 7.868 www.irjmets.com

GESTURE-GUIDED CAMPUS COMMUNICATION: REVOLUTIONIZING COLLEGE NOTICE BOARDS WITH DEEP LEARNING

Disha Balsaraf*1, Samruddhi Auti*2, Muskan Chaugule*3, Hinge Rasika*4, A.S. Magar*5

*1,2,3,4,5Computer Department, Jaihind Polytechnic, Kuran, India.

ABSTRACT

Recent developments in seamless connectivity and ubiquitous availability of electronic gadgets have resulted in a major improvement in the internet's environment. Improvements to existing infrastructure, including technology developments, allow for enhanced convenience. These creative applications have contributed to the expansion of the electronic sector. Using notice boards is not as appealing as an interactive LCD panel.

The notice board uses computer vision technology to recognize gestures and enable for gesture navigation. The suggested approach successfully implements convolutional neural networks, enabling gesture-based notice board navigation. The problem with these applications is that they lack reliable accessibility capabilities that allow handicapped users to access the notice board. Other systems, such as notice boards at schools and colleges, were built to perform traditionally but can be significantly improved by incorporating technology. If you utilize this extremely useful and convenient technique for a notice board, you will discover that reading information on an LCD screen is much more pleasurable and profitable.

Keywords: Approach, Gesture, Convolutional Neural Networks, Board, Notice.

I. INTRODUCTION

The hand is the most useful instrument for human involvement since it is the limb with the most physical and functional mobility. Because it allows humans to communicate with software applications in a more organic and intuitive manner, as well as its versatility in a variety of situations, incorporating hand gestures as a functionality into human-computer interaction initiatives may prove advantageous. This is because it enables humans to connect with software applications in a more logical and clear manner. In other words, including hand gestures as a practical component in HCI applications may be advantageous. Therefore, it shouldn't be It's remarkable that gesture detection is one of the most important issues in spontaneous human-computer interaction right now.

Convolutional Neural Networks (CNNs) have transformed several industries, particularly image identification and computer vision jobs. At their core, CNNs replicate the behaviour of the human visual system by efficiently extracting characteristics from images via a sequence of convolutional layers.

To properly use CNNs, one normally begins by specifying the architecture, which includes the number of layers, their types (convolutional, pooling, etc.) and parameters. These layers use methods like convolution, activation, and pooling to gradually learn hierarchical representations of the input data.

Train a CNN by feeding it labelled data, known as the training set, and modifying the network's weights using backpropagation and optimization algorithms such as stochastic gradient descent. This process iterates until the model achieves a suitable degree of accuracy. Once trained, The CNN can be used for a variety of tasks, including segmentation, object identification, and picture categorization, once it has been learned. The neural network processes input photos for deduction, and its result shows predictions and categorizations based on the attributes that the network has learned. Furthermore, by retraining only some of the components of a model that has been trained with job-specific information, any pre-trained model can be modified for a new task, thereby fine-tuning CNNs for that particular tasks. This process is known as transfer learning. This method works particularly well in situations where there is a lack of data with labels or where starting from scratch would be computationally costly. In conclusion, CNNs provide a strong framework for identifying and deriving complex patterns from visual input, opening up a variety of uses in a variety of sectors, including security, cultural activities, and even healthcare and autonomous cars.

Deep Convolutional Networks, often known as Convent's, are a type of neural network design designed for analysing and interpreting grid-like data, specifically photographs. These neural networks have numerous layers, include convolutional, stimulation, pooling, and fully linked layers. Deep Convolutional Models use convolutional processes to gather layered characteristics in images that are input, including all low-level information and a high-level semantics. Deeply structures with several layers enable these networks to learn complicated representations of visual data, resulting in greater performance in tasks such as picture classification, object detection, and semantic segmentation. These networks' depth enables them to capture nuanced patterns and fluctuations in information, making them extremely useful in applications in the real world. Deeply Convolutional neural networks are now key tools in the field of computer vision, driving improvements in areas. Their capacity to learn on its own and identify characteristics from raw pixel data has catapulted them into the cutting-edge of AI research and applications.

Because it represents the limb with the greatest degree of mobility, both functionally as well as physically, the hand is the most valuable tool for human interaction. The integration of hand motions as a kind of function into interaction between humans and computers initiatives could prove beneficial because it allows people to interact with programs in a way that feels more natural and intuitive and because it can be used in a variety of situations. The reason for this is that it gives people a chance to interact with software programs in a way that seems more rational and succinct. Stated differently, it may be advantageous to include gestures with the hands as a useful element in HCI applications. Therefore, it must not be It's remarkable that hand recognition is one of the most important issues in unexpected interactions between people and computers right now.

According to the circumstance, hands might depict fluid or fixed feelings. Given that the structure of the hand expresses stationary hand movements, complex hand arrangements are likely required to represent a wide variety of distinct fixed hand movements. This is because the arm's geometry transmits hand movements that remain stationary. On the other hand, because active hand gestures include hand shape and motion, the limitations imposed by hand movements are upheld less rigorously. As a result, kinetic hand gestures incorporate both hand appearance and movement. This has been a discernible rise in the amount of individuals interested in creating devices during the past few years.

Hand motions can be identified using either vision-based methods or data-based gloves, both of which are now in use. This shows that it is possible to do so. Because there aren't many electronic gloves available for purchase right now, and those that are may be prohibitively expensive and limit the wearer's ability to use the hands simply in their trade, the majority of research on hand motion recognition has depended on computers with vision systems rather than electronic gloves. This is owing to the limited number of electronic gloves available on the market today. Recent research has focused on the framework of gesture-based interactions between people and machines. This is because... The fundamental elements that people use to communicate essential data are movements.

Gestures made with the hand are commonly used and understood easily by people, therefore it is possible to incorporate them into an intuitive interface for machines (HMI). This is related to the reality that individuals are very comfortable with hand gestures. Although some academics have attempted to do so in the past, it is extremely unlikely that something such as digital gloves will be used for the purpose of collecting information about hand gestures on a large scale due to the high cost of the necessary equipment. As a result, current research has led to the creation of image-based algorithms for identifying hand gestures using low-cost imaging sensors.

II. LITERATURE REVIEW

1. D. Ryumin et al. proposed a design for an intelligent robot cart for supermarkets featuring a display and an interactive user experience incorporating spoken language and acoustical voice detection, as well as a software platform for collecting sign languages datasets using the Kinect 2.0 device. The collected corpus. The Ruslan features audio of 13 realistic Russian sign language signers. Each signer repeated the exact same 164 lines five times.
2. Preeti Mehra employed text mining in this study to provide a consistent interpretation of phrases in the retail industry, which has been adopting gesture control technologies. For analysing information gathered from retail customer assessments, a two-step technique was employed, first extracting keywords using text analysis and then grouping these phrases into clusters. Shops have utilized gestures control systems in an array of methods, such Kinect with Microsoft Store Purchasing, 'Gesture Control Screen,' 'Online Fittings The accommodations,' 'Retailing Interaction Feel Screens,' "Use of Visible Reflections,' and 'enhanced realities window show'.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:04/April-2024 Impact Factor- 7.868 www.irjmets.com

3. Y. Shimizu et al. presented an interactive informational assistance system for the rental bicycle sector, developed in partnership with an organization in Tokyo's Oku-tama district. The researchers utilized two different types of robotic collaborators: a staff member and a humanoid creature equipped with a tablet PC. Each robot friend has a particular role to play in communication and recommendation. Firstly, the authors should discuss what robots and humans should do when delivering customer service.
4. D. Wu et al. proposed a new Deep Dynamic Neural Network to perform continuous gesture identification on multimodal data, including picture, depth, and skeletal features. Unlike previous state-of-the-art systems, the authors are not dependent on handcrafted features, which are laborious to generate, particularly when done individually for every input channel [4]. However, deep neural networks are employed to extract pertinent details from information.
5. A deep learning paradigm for social classification was proposed by T. Du et al. As a replica of the organic neural network technique framework, deep learning has considerable research value and offers powerful feature extraction and classification skills. Regardless of the method or application orientation, it is crucial to recognize human body motion utilizing the deep learning algorithm for superior intelligence and the collected data on human movements.

III. PROPOSED METHODOLOGY

A. Problem Statement

To achieve accurate and effective navigation of the notice board using gesture by the use of image processing through the implementation of Convolutional Neural Networks.

B. Motivation

For decades, bulletin boards have served as a trustworthy and effective means of delivering information. They enable the display of information in a way that end users can understand and access. Many educational organizations, including schools and colleges, rely heavily on these boards for communication and information dissemination. However, as the variety of colleges and universities, institutes, and other organizations grows, so does the amount of information displayed on the notice board. With plenty more to show, the noticeboard is soon becoming inadequate. As a result, an accurate and practical system is necessary to store more data and provide navigational capabilities via gesture recognition on a digital notice board.

C. System Overview Diagram

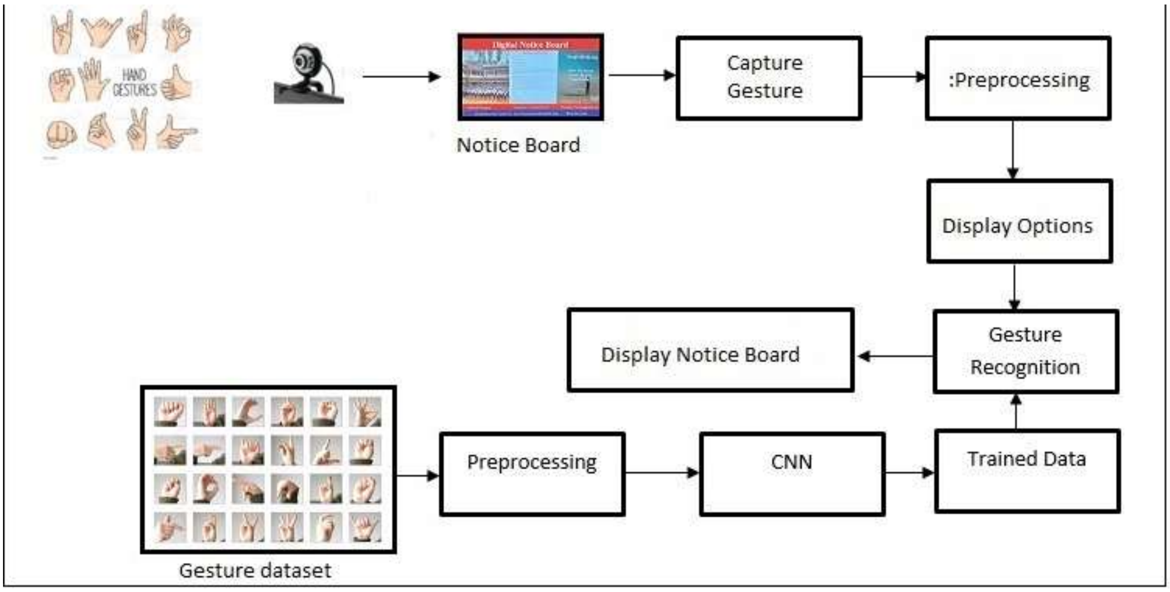

Figure 1: System Overview Design

The system overview diagram provides an overview of the system with the important modules in the form of blocks. At first the user provides the Gesture dataset which is pre-processed and the images are normalized before sending to the Convolutional Neural Networks to achieve the trained data. The user then provides the live feed the frames from which are grabbed and pre-processed following that the CNN trained data is deployed. The Fuzzy classification is utilized which results in the Gestures.

D. Module Description

1) **Module A:** Preprocessing

- Image Scaling
- Image Sharing
- Image Restoration
- Dataset List Formation

2) **Module B:** Image Normalization

- Pixel Position
- Color Position
- Model feature
- Region Estimation

3) **Module C:** Convolutional Neural Network

- ROI Extraction
- First Layer Convolution
- Fully Connected Layer
- Convolution Layer

4) **Module D:** Decision Making

- Prediction Score
- Protocol Estimation
- If-then rules
- Automatic Interface Handling for Notice Board

The proposed methodology for the purpose of achieving effective and useful realization of the gesture based notice board has been depicted in the figure 1 above and the steps taken to achieve this system are elaborated below.

Step 1: Preprocessing – The initial part of the procedure entails taking images of the hand gestures using the assistance of OpenCv. The VideoCapture method within the cv2 package takes images of the intended gesture of the hand for the purpose of navigating the notice board. Among the most prevalent hand gestures are previous, next, enter, back and blank. The gestures are based on the interactive graphical user interface that is designed using the java swings framework.

The user interface will be presented to the student of engineering with the respective sections of 4 years. The student will select the respective year, following which the two semesters for that year will be indicated for the student's selection. Following the successful selection the students can then view the notices and navigate for the next, or previous one or go back to the year and semester selection using the respective gestures. The gestures are captured by utilizing YCbCr color space, the hand's complexion is identified, and the respective region will be sliced out of the image. When the respective gesture of the hand has been recognized, it is resized, and a grayscale transition is done. The final outcome is a grayscaled modification of the source image. The image, is then subsequently shrunk by scaling to 96x96, and is going to be stored in a specified gesture subfolder. Every single of the five gestures is captured through the same procedure up until the purpose of gathering the input collection is fulfilled by achieving the requisite amount of gesture images for each of the gestures.

Step 2: Image Segmentation – Before reaching this point, the user did not have access to any means by which they were able to investigate the input dataset. However, this ability has been reached after the successful collection of the gestures in the previous step. The images were gathered especially for the intent of creating this dataset and its accompanying segregations. Both the training generator as well as the validation generator are going to collaborate together to execute through these procedures in an integrated manner. The training generator comprises a batch size of 64, requires an image size of 96 pixels on each side, and employs a monochromatic color scheme with a classification-class configuration. This parameter are used in the

IRJMETS

e-ISSN: 2582-5208

International Research Journal of Modernization in Engineering Technology and Science

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

Volume:06/Issue:04/April-2024 Impact Factor- 7.868 www.irjmets.com

construction of the training generators. The desired validation generator will have an architecture that has components that are equivalent to the training generator. These choices feature a batch size of 64, a target image size of 96 x 96 pixels, and a scheme of colors in grayscale as well as categorization class selection. The batch size is adjusted to set to 64, and the intended picture size can be set to 96 by 96 pixels. Additionally, there are 64 batches for this stage of the procedure.

Step 3: Convolution Neural Network – This corresponds to the most important aspect of the suggested approach because of its fundamental position in the framework, which is to recognize and categorize the many different types of gestures made with the hands. The very first image is what is referred to as a stimulus for each individual constituent of the convolutional Neural Network. In this method, the network is trained using images that have been gathered, pre-processed, and categorized before being fed into it. The training image directories and the test image directories have been incorporated in the input dataset by a 50-50 split. After this, the files included inside each directory are then divided into their respective subdirectories, with each subdirectory reflecting a unique hand gesture and the images that correlate to it. Through the whole of the procedure's training phase, these images will continue to be fed into the CNN's core computational architecture. Due to this the system is required to edit the images so that they have an identical height and width of 96 pixels prior moving further with the process. The network was trained employing all of these images for an aggregate of 500 epochs alongside a batch size of 64 with a density of 5. This was done on the premise that the system could only be handling a maximum of five distinct gestures in this instance. In all, there were actually 64 batches, and the density was approximately 5. TensorFlow and Keras are a pair of add-on libraries for the Python programming language that make it easier to develop convolutional neural networks. These improvements are what make it possible for CNN to include a wide variety of components. The entirety of the design can be seen in Figure

Layer	Activation
Conv 2D 32x3x3	ReLU
Conv 2D 32x3x3	ReLU
MaxPooling2D 2x2	
Droupout 0.25	
Conv 2D 128x3x3	ReLU
MaxPooling2D 2x2	
Conv 2D 128x3x3	ReLU
MaxPooling2D 2x2	
Droupout 0.25	
Flatten	
Dense 1024	ReLU
Droupout 0.25	
Dense 5	Softmax
Adam Optimizer	

Figure 2: CNN Network Architecture

CNN network Architecture After that, the freshly built deep convolutional neural network is put through training for a total of five hundred epochs employing the architecture. Following the completion of the training process, a file containing the extension h5 is obtained.

Step 4: Decision Making – Following the conclusion of the CNN-based learning technique, the system may be evaluated further for its capability of recognizing hand gestures for the purpose of navigating a notice board. This assessment may be carried out following the CNN based learning approach has been finished in its entirety. The OpenCV framework is employed to power up the digital camera and commence recording operations in order to make an effort at capturing hand gestures. After that comes the process of cropping,

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:04/April-2024 Impact Factor- 7.868 www.irjmets.com

which is done in accordance with the hand gestures that were originally captured on camera for the training process. So to ensure it is able to be implemented in combination with the other components of the.h5 file, the physical dimensions of the images that is presently being demonstrated have been shrunk. The images is then modified by having its color changed to grayscale, and its border has been eliminated. These modifications have been made to enable the image to be utilized further using the trained .h5 file. After finishing this procedure, the relevant hand gesture, along with all of the additional hand gestures that correlate, will be collected simultaneously in preparation for being sorted into the appropriate category. If the count for that gesture reached is greater than a certain threshold that has been set intrinsically, then the action is deemed to have been observed and carried out for the navigation of the notice board. If the score that would have been attained is lower than the threshold, then the act in question isn't regarded as having been observed and the system will continue capturing the images for the gesture recognition for navigating the notice board.

IV. RESULT

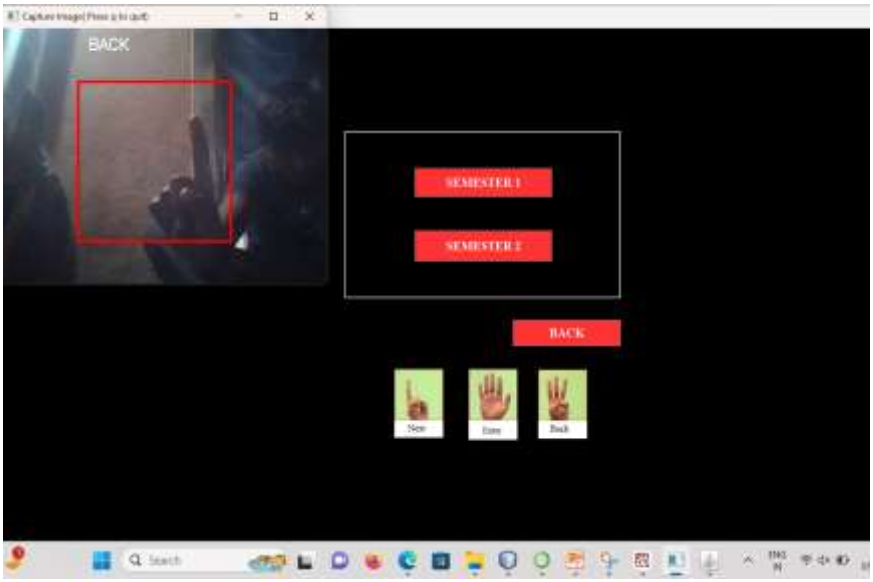

Figure 3:

Figure 4:

V. CONCLUSION

As a result, the environment of the internet has significantly improved as a result of the latest developments in seamless connectivity and the general availability of electronic gadgets. Convenience can be enhanced by incorporating technological advancements into the current infrastructure. The electronic sector has grown as a result of these inventive applications. An interactive LCD panel is more visually appealing than using notice boards the old-fashioned way. This method is really simple and helpful. Using an electronic notice board to find information is a far more enjoyable and satisfying experience. The problem with these technologies, though, is that they lack any dependable accessibility features that would allow people with disabilities to view the notice board.

VI. FUTURE SCOPE

This approach can eventually be improved to function in universities and schools, which will make it easier to observe notice boards.

VII. REFERENCE

[1] D. Ryumin, D. Ivanko, A. Axyonov, I. Kagirov, A. Karpov and M. Zelezny, "Human-Robot Interaction with Smart Shopping Trolley Using Sign Language: Data Collection," 2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), 2019, pp. 949-954, DOI: 10.1109/PERCOMW.2019.8730886.

[2] Preeti Mehra and Balpreet Kaur, "Gesture Recognition: towards Making Future Retail Buying Experience Stimulating," International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8 Issue-6, March 2020.

[3] Y. Shimizu, S. Yoshida, J. Shimazaki, and N. Kubota Kubota, "An Interactive Support System for Activating Shopping Streets using Robot Partners in Informationally Structured Space," 2013 IEEE Workshop on Advanced Robotics and its Social Impacts, pp. 70-75, DOI: 10.1109/ARSO.2013.67055.

[4] D. Wu et al., "Deep Dynamic Neural Networks for Multimodal Gesture Segmentation and Recognition," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 8, pp. 1583-1597, 1 Aug. 2016, DOI: 10.1109/TPAMI.2016.2537340.

[5] T. Du, X. Ren, and H. Li, "Gesture recognition method based on deep learning," 2018 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC), 2018, pp. 782-787, DOI: 10. 1109/YAC.2018.84064