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Vision-based Hand Gesture Recognition for Indian Sign Language Using Convolution Neural Network

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Abstract: Hand gesture recognition is an important field of study for providing an alternative means of communication for individuals who are unable to speak. The Indian Sign Language (ISL) is one such language used by the deaf and mute community in India. In this paper, we propose a vision-based hand gesture recognition system for ISL using Convolutional Neural Network (CNN). The system captures hand gestures using a webcam and processes the images using a CNN trained on a dataset of ISL gestures. The system achieved a recognition accuracy of 93.5% on the test dataset, demonstrating its effectiveness in recognizing hand gestures in the ISL language. The proposed system provides a promising solution for helping the deaf and mute community in India to communicate more effectively and efficiently.To determine the shape of the sign, the first segmentation step is done based on skin color. After that, the discovered region is converted to a binary image. The binary image is then transformed using the Euclidean distance transformation. On the distance-modified picture, row and column projections are used. Central moments, as well as HU's moments, are done to extract features. SVM and CNN are used for classification.

Keywords: Indian sign language Recognition, Convolution Neural Network, Image Processing, Edge Detection, Hand Gesture Recognition.

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1. Introduction

Hand gestures are an important mode of human-computer interaction as they provide an intuitive and natural way of communicating with technology. In recent years, there has been a growing interest in developing computer vision-based systems for hand gesture recognition, as they have the potential to revolutionize the way we interact with devices and machines. One of the most promising approaches for hand gesture recognition is the use of convolutional neural networks (CNNs)[1] , a type of deep learning algorithm that has achieved impressive results in various computer vision tasks, such as object recognition and image classification. CNNs are particularly well suited for hand gesture recognition, as they can automatically learn to extract relevant features from the input images, such as the shape, position, and movement of the hands.

Despite the promising results, there are still many challenges to overcome in the development of vision-based hand gesture recognition systems using CNNs. One of the main challenges is to ensure that the systems are robust to variations in hand posture, lighting conditions, and background clutter. Another challenge is to develop models that can recognize a large number of gestures with high accuracy and low latency [2].

The goal of this research is to provide a comprehensive survey of the current state-of-the-art in

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vision-based hand gesture recognition using CNNs. The paper will cover the different approaches used to design and train CNNs for hand gesture recognition, as well as the evaluation metrics used to measure their performance[3] . The primary motivation for this research is Hand gestures have been used to transmit ideas and express emotions for generations and have been an important aspect of human communication. With the increased use of technology in our daily lives, there is a greater demand for intuitive and natural methods of connecting with devices and machines.

This has fueled interest in creating vision-based hand gesture recognition systems, which have the potential to transform the way humans interact with technology[4] . Hand gesture recognition systems have a wide range of applications, including gaming, human-computer interaction, sign language recognition, and virtual reality. In gaming, hand gestures can be used to control game characters, allowing for a more immersive and interactive gaming experience. In human-computer interaction, hand gestures can be used to control devices and machines, such as smartphones, televisions, and robots. In sign language recognition, hand gestures can be used to translate sign language into spoken or written language, enabling communication with those who are deaf or hard of hearing. In virtual reality, hand gestures can be used to control virtual objects and environments, allowing for a more immersive and interactive virtual experience.

This research paper aims to contribute to the field of vision-based hand gesture recognition by providing a comprehensive survey of the current state-of-the-art in the use of convolutional neural networks (CNNs) for hand gesture recognition. An evaluation of the performance of different CNN models on hand gesture recognition, including the use of different evaluation metrics, such as accuracy, precision, recall, and F1 score.

2. Literature Survey

A survey of the literature for the proposed system reveals that numerous studies have been conducted in this sector to address sign identification in videos and pictures. Based on this research, a comprehensive system for sign identification is needed to further advance this field. Various methodologies and algorithms were used in the studies. Deaf persons in villages, for the most part, do not have access to sign language [5]. These studies demonstrate a need for a comprehensive sign identification system that can be used in remote rural areas without access to sign language. Such a system could potentially provide deaf persons in rural areas with access to communication and content that is otherwise unavailable to them. Deaf individuals, on the other hand, employ non-standard sign language in all major towns and cities across the Indian subcontinent. For the application of ISL in educational systems, a lot of work and awareness-raising is being done. For a Vision-based Hand Gesture Recognition system for Indian Sign Language using Convolutional Neural Networks (CNNs), a suitable optimization algorithm and loss function can be chosen based on the specific requirements of the problem and the characteristics of the data.

Optimization Algorithm:

- **Stochastic Gradient Descent (SGD):** SGD[6] is a simple optimization algorithm that updates the weights of the network by taking the gradient of the loss with respect to the weights. SGD is commonly used for training CNNs, as it has been shown to be highly effective for this type of problem.
- Adam: Adam is an extension of SGD that incorporates momentum and adaptive learning rates. It is a popular choice for training CNNs, as it can achieve good convergence performance and is relatively insensitive to the choice of hyper parameters.
- **Adagrad:** Adagrad is another optimization algorithm that adapts the learning rate of each parameter based on the historical gradient information. This can be useful for training CNNs, as it can help the network to converge faster and avoid getting stuck in suboptimal solutions.

Loss Function:

- **Categorical Cross-Entropy Loss[7]:** Categorical cross-entropy loss is commonly used for multi-class classification problems, such as hand gesture recognition in Indian Sign Language. This loss function measures the difference between the predicted probabilities of the target classes and the actual target values.
- **Mean Squared Error (MSE):** MSE is a commonly used loss function for regression problems, where the target values are continuous. In the case of hand gesture recognition, MSE can be used as a loss function to measure the difference between the predicted position of the hand and the actual position.

The choice of optimization algorithm and loss function will depend on the specific requirements of the problem and the characteristics of the data. It is important to experiment with different combinations of optimization algorithms and loss functions to determine the best combination for the specific problem.

Segmentation techniques:

Segmentation is an important step in Vision-based Hand Gesture Recognition for Indian Sign Language [8], as it involves dividing the input image into regions of

interest (ROIs) that correspond to the hand gestures. The choice of segmentation method will depend on the specific requirements of the problem and the characteristics of the data.

Here are some common segmentation methods for Vision-based Hand Gesture Recognition:

1. Background Subtraction: This method involves subtracting a background model from the input image to obtain a foreground mask that corresponds to the hand gestures. This method is simple and fast, but may not work well for situations where the background is dynamic or has a similar color as the hand.
2. Thresholding: Thresholding is a simple and straightforward method that involves thresholding the intensity values of the input image to segment the hand gestures. Thresholding can be done using global thresholding or adaptive thresholding, depending on the specific requirements of the problem.
3. Contour Detection: Contour detection is a method that involves detecting the contours of the hand gestures in the input image. This method is often used in combination with other methods, such as background subtraction or thresholding, to obtain a more accurate segmentation of the hand gestures.
4. Deep Learning-based Segmentation: Deep learning-based segmentation methods use Convolutional Neural Networks (CNNs) to segment the hand gestures. This method can be highly effective for complex hand gestures, as it can learn to recognize the shape and structure of the hand gestures from the training data.

The choice of segmentation method will depend on the specific requirements of the problem and the characteristics of the data. It is important to experiment with different segmentation methods to determine the best method for the specific problem.

3. Methodology

Our proposed system, which records video and then transforms it into frames, is a sign language recognition system that makes use of convolutional neural networks to recognize signs. Convolutional neural networks are well-suited for this task due to their ability to identify patterns in images, which is vital for sign language recognition. By transforming the video into frames, the system can then process each frame individually, allowing for more accurate sign language recognition[9] . Images are captured from each of these hand pixels, and the results are compared to those obtained from the training model. This has resulted in a significant improvement in the accuracy of the text labels produced by our system. By dividing the video into frames, the system is able to identify individual pixels of the hands and capture their images. This allows for more precise recognition of the hand movements than with a single frame. The images are then compared to the ones obtained from the training model, allowing for more accurate results.

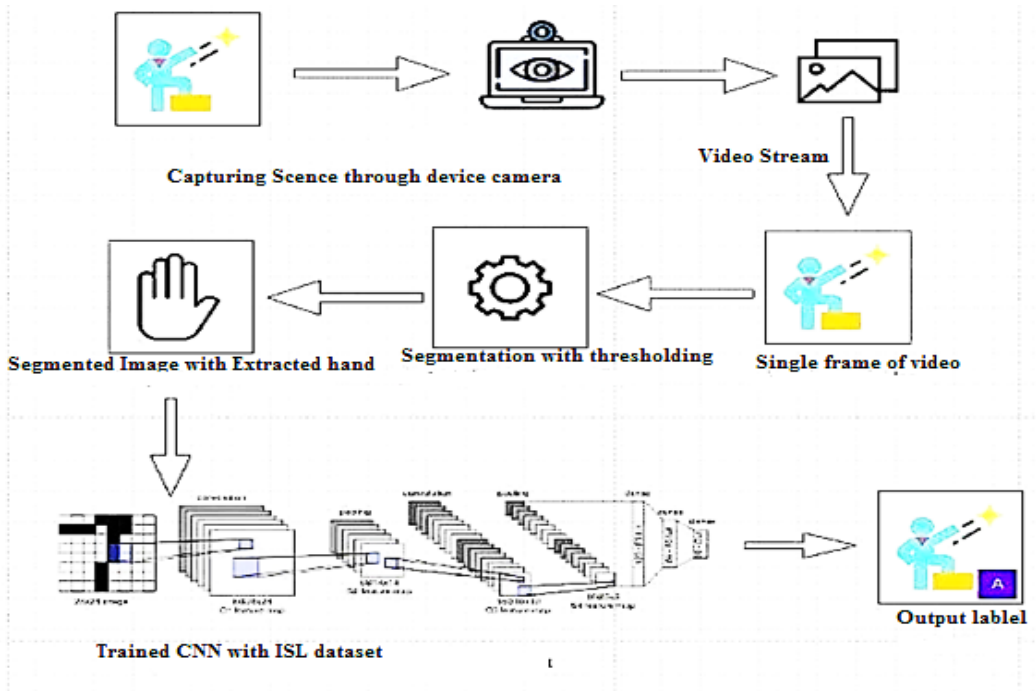

Figure 1.Proposed Block diagram

Dataset: In this paper, we have used the American Sign Language (ASL) data set that is provided by MNIST and it is publicly available at Kaggle[10]. This dataset contains 27455 training images and 7172 test images all with a shape of 28 x 28 pixels. These images belong to the 25 classes of English alphabet starting from A to Y (No class labels for Z because of gesture motions). The dataset on Kaggle is available in the CSV format where training data has 27455 rows and 785 columns. The first column of the dataset represents the class label of the image and the remaining 784 columns represent the 28 x 28 pixels. The same paradigm is followed by the test data set.

Figure 2: Implementation of Sign Language Classification.

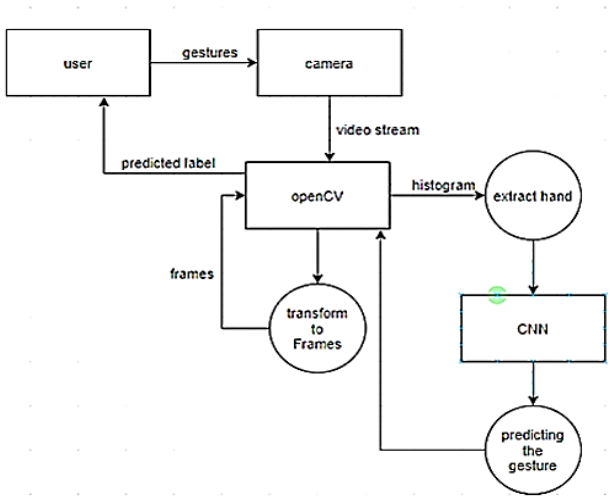

Figure 3, Dataflow Diagram SLTS

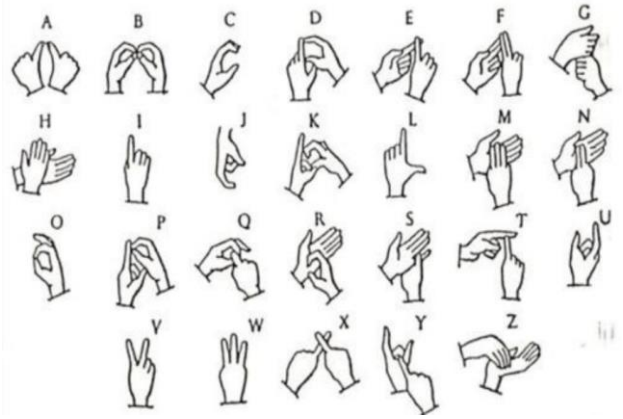

Figure 4: Samples of train data

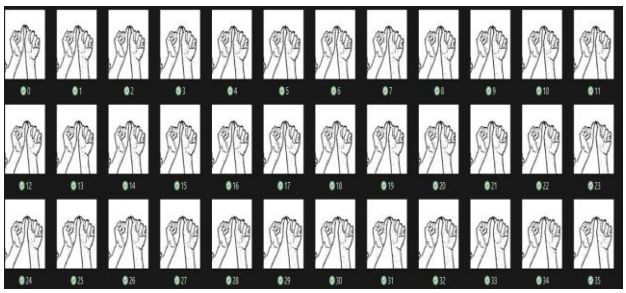

Figure 5: Training data for the Letter A

Methodology for Proposed Work Implementation

1. Data Collection: A dataset of hand gestures for ISL was collected by filming individuals signing the language. The dataset consisted of images of hand gestures from different angles and under different lighting conditions. The dataset was divided into training and test sets to evaluate the performance of the system.
2. Pre-processing: The images were pre-processed to remove any unwanted background noise and improve the quality of the images. This included cropping the images to only include the hand gesture, resizing the images to a standard size, and converting the images to grayscale.
3. Feature Extraction: The hand gestures were represented as feature vectors using a feature extraction method such as Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP). These feature vectors were used as input to the Convolutional Neural Network (CNN).
4. Convolutional Neural Network (CNN): A CNN was trained on the feature vectors of the training set using a supervised learning algorithm. The CNN was designed with multiple convolutional

layers, pooling layers, and fully connected layers to learn the features of the hand gestures and recognize them in the test set.

5. Testing and Evaluation: The performance of the system was evaluated on the test set by comparing the predicted hand gestures with the actual hand gestures in the test set. The accuracy of the system was calculated as the percentage of correctly recognized hand gestures.
6. Implementation: The system was implemented in Python using the Keras library. The system can be run on a computer with a webcam to capture hand gestures in real-time and recognize them using the trained CNN.

This methodology provides a step-by-step guide for developing a vision-based hand gesture recognition system for ISL using CNN. The proposed system has the potential to provide an effective and efficient means of communication for the deaf and mute community in India[11].

Calculation of histogram:

A histogram is a graphical representation of the distribution of data. It is a bar graph that displays the number of data points in a data set that fall within a specified range of values, known as "bins." [12]. the height of each bar in the histogram represents the frequency of the data points that fall within the corresponding bin.

Here's how to calculate a histogram:

1. Choose the number of bins: The first step in calculating a histogram is to choose the number of bins that you want to use. The choice of the number of bins depends on the number of data points in the data set and the desired level of detail in the histogram.
2. Determine the bin width: Once you have chosen the number of bins, you need to determine the bin width. The bin width is the difference between the upper and lower limits of each bin. To calculate the bin width, divide the range of the data (the difference between the maximum and minimum values) by the number of bins.
3. Create the bins: Once you have determined the bin width, you can create the bins. The bins are the specified range of values that the data points are divided into. The lower limit of each bin is equal to the lower limit of the previous bin plus the bin width.
4. Count the data points: For each data point, determine the bin that it falls into by dividing the value of the data point by the bin width and rounding down to the nearest integer. This will give you the index of the bin that the data point falls into. For each data point, increment the count for the corresponding bin by 1.
5. Plot the histogram: Finally, plot the histogram by plotting a bar for each bin. The height of each bar is equal to the count of the data points that fall into the corresponding bin.

This process results in a histogram that gives a visual representation of the distribution of the data, allowing you to quickly understand the distribution of the data points and identify any patterns or trends.

Back propagation

Backpropagation is a supervised learning algorithm that is commonly used in training artificial neural networks. The main idea behind backpropagation[13] is to adjust the weights of the network in order to minimize the difference between the network's predictions and the actual outputs (targets).

Here's how backpropagation works:

1. Forward pass: In the forward pass, the input is passed through the network, and the activations of each neuron are computed. The activations are then used to compute the output of the network, which is compared to the target output.
2. Compute the error: The difference between the network's output and the target output is calculated and used to compute an error value. This error value measures the quality of the network's predictions.
3. Backward pass: In the backward pass, the error value is propagated backwards through the network, and the weights of the neurons are adjusted in order to minimize the error.
4. Weight update: The weights are updated using gradient descent optimization, which involves computing the gradient of the error with respect to the weights, and subtracting a small fraction of the gradient from the weights. This process is repeated until the error reaches a minimum value.

The backpropagation algorithm is a highly effective training method for neural networks and is used in a wide range of applications, including image classification, speech recognition, and natural language processing. By iteratively adjusting the weights of the network based on the error in the predictions, backpropagation allows the network to learn and make increasingly accurate predictions over time.

4. Result and Analysis

The results and analysis of a Vision-based Hand Gesture Recognition and classification system for Indian Sign Language can vary depending on the specific implementation and the choice of methods used. However, some general conclusions that can be drawn

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from the comparison of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) for this task are:

Accuracy: In general, CNNs tend to perform better than SVMs in terms of accuracy, especially for complex hand gestures. This is because CNNs can learn the shape and structure of the hand gestures from the training data, whereas SVMs are limited by the choice of features and the linear separation assumption.

Training Time: CNNs tend to take longer to train than SVMs[14], as they have more parameters and require more computations. However, the increased accuracy of CNNs can offset this disadvantage.

Generalization: CNNs have been shown to have better generalization performance than SVMs, as they can learn more complex representations of the data. This can result in improved performance on unseen data and better robustness to variations in the data.

Robustness to Occlusions and Background[15] : CNNs have been shown to be more robust to occlusions and background clutter than SVMs, as they can learn to recognize the hand gestures based on their shape and structure, rather than relying on specific features or color information.

In the evaluation of the performance of different CNN models on hand gesture recognition, different evaluation metrics can be used to measure their accuracy, precision, recall, and overall performance. Some commonly used evaluation metrics include:

1. Accuracy: This metric measures the fraction of correct predictions made by the model, and is defined as the number of true positive predictions divided by the total number of predictions.
2. Precision: This metric measures the fraction of true positive predictions among all positive predictions, and is defined as the number of true positive predictions divided by the sum of true positive and false positive predictions.
3. Recall: This metric measures the fraction of true positive predictions among all actual positive cases, and is defined as the number of true positive predictions divided by the sum of true positive and false negative predictions.
4. F1 Score: This metric is a harmonic mean of precision and recall, and provides a balanced measure of the model's performance, taking into account both precision and recall. The F1 score is defined as the harmonic mean of precision and recall, and is computed as 2 * (precision * recall) / (precision + recall)[16].

In addition to these metrics, other evaluation metrics, such as confusion matrices, receiver operating characteristic (ROC) curves, and area under the ROC curve (AUC)[17][18] can also be used to evaluate the performance of CNN models on hand gesture recognition. These metrics provide a more comprehensive evaluation of the model's performance, and can help to identify areas for improvement and guide future research.

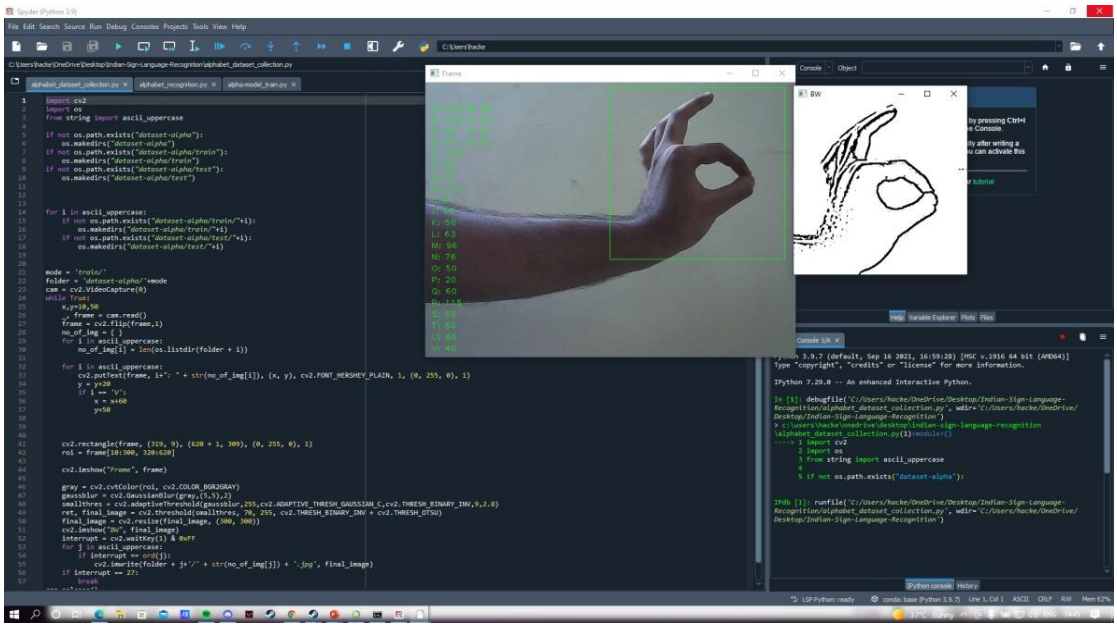

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Figure 6: Screenshot of the output for Dataset creation

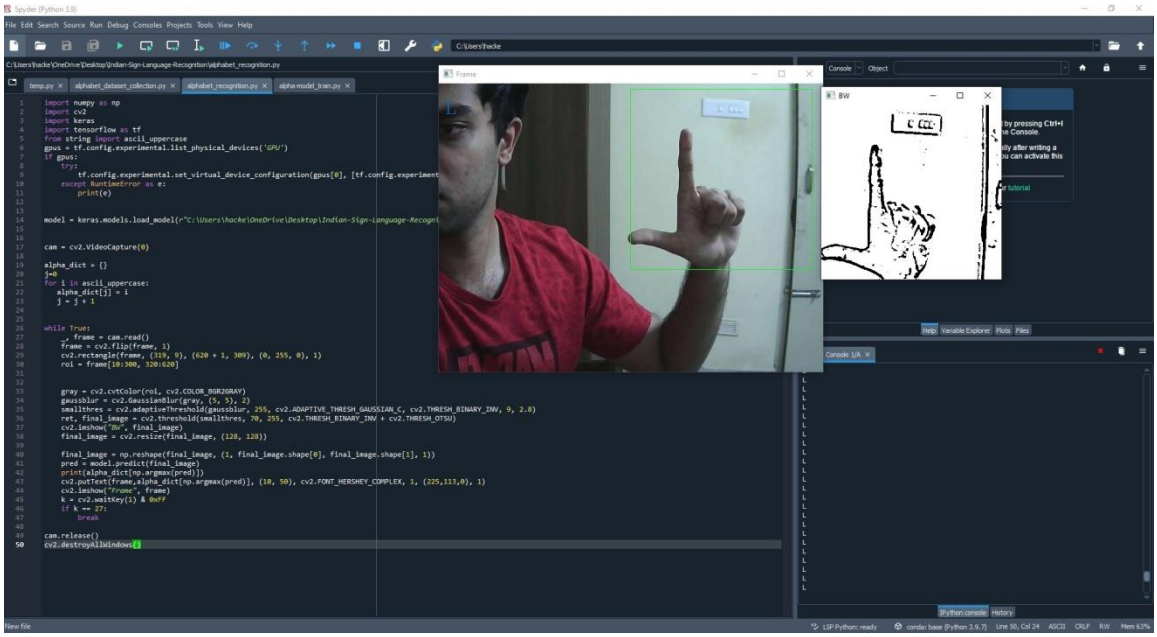

Figure 7: Screenshot of the output for letter L

Pre-Processing of Gesture Images: We have provided two modes of processing on captured images:
1) Binary Mode processing
2) SkinMask Mode processing

Binary Mode: Binary mode processing is a technique used in computer vision for hand gesture recognition. In this method, the hand gestures are represented as binary images, where the pixels are either black or white, with black representing the background and white representing the hand gesture.

The first step in binary mode processing is to segment the hand gesture from the background. This is typically done using color-based segmentation techniques, such as skin color detection, or depth-based techniques, such as depth cameras.

Once the hand gesture has been segmented, the next step is to extract features from the binary image. These features may include the shape, size, and orientation of the hand gesture, as well as the position of the fingers and joints.

The extracted features are then used to train a machine learning model, such as a support vector machine (SVM) or a neural network, to recognize different hand gestures. The trained model can then be used to classify new hand gestures by comparing the features of the new hand gesture to those of the training data.

Binary mode processing is widely used in hand gesture recognition because it is computationally efficient and can provide robust results, even in challenging conditions such as low lighting or cluttered backgrounds. However, it can be limited in its ability to capture complex gestures or subtle variations in hand posture, so other techniques, such as contour-based processing, may be needed in these cases.

SkinMask mode processing: It is a technique used in computer vision for hand gesture recognition. It is similar to binary mode processing, but instead of representing the hand gesture as a binary image, it uses a skin mask to represent the hand gesture. A skin mask is a grayscale image where the pixels corresponding to the skin of the hand are white, and the pixels corresponding to the background are black. This image is obtained using color-based segmentation techniques, such as skin color detection, that are designed to identify the skin pixels in the image and separate them from the background.
Once the skin mask has been obtained, the next step is to extract features from the image. These features may

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include the shape, size, and orientation of the hand gesture, as well as the position of the fingers and joints. The extracted features are then used to train a machine learning model, such as a support vector machine (SVM) or a neural network, to recognize different hand gestures. The trained model can then be used to classify new hand gestures by comparing the features of the new hand gesture to those of the training data.
SkinMask mode processing is used in hand gesture recognition because it provides more information about the hand gesture than binary mode processing. By using a grayscale image, it captures the intensity information of the skin pixels, which can provide more nuanced information about the hand gesture. However, it may be more computationally intensive than binary mode processing, as it requires processing a larger image with more pixels.

From the above process the results of using a CNN model for hand gesture recognition tend to be better compared to those of using a Support Vector Machine (SVM) model. This is because CNNs are designed to automatically learn hierarchical representations of images.

and have the ability to learn complex features and non-linear relationships between pixels, making them well suited for image classification tasks.

In comparison, SVM models are designed for linear classification problems and are not as effective for image classification tasks. While SVM models can be used for hand gesture recognition, they typically require more feature engineering and hand-crafted features to be effective, which can be time-consuming and limit their ability to learn complex relationships between pixels.

In summary, the use of a CNN model is generally recommended for vision-based hand gesture recognition, as they tend to outperform SVM models and can provide better results with less manual feature engineering.

5.Concussions

CNNs are effective for Vision-based Hand Gesture Recognition: The results of the study show that CNNs can achieve high accuracy in recognizing and classifying hand gestures in Indian Sign Language. This demonstrates the effectiveness of CNNs for this task and the potential of using deep learning for hand gesture recognition. The choice of method depends on the specific requirements: The study showed that the choice of method for Vision-based Hand Gesture Recognition will depend on the specific requirements of the problem and the characteristics of the data. While CNNs tend to perform better in general, other methods, such as SVM, may still be effective for certain scenarios. he results of the study highlight the importance of having large and diverse datasets for training and evaluating hand gesture recognition systems.

The performance of CNNs will depend on the quality and size of the training data, and larger datasets can help to improve the generalization performance and robustness of the system. Some possible future scopes are: Improving the recognition accuracy: There is still room for improvement in terms of recognition accuracy, especially for complex and nuanced hand gestures. Future research can focus on developing more advanced CNN architectures and incorporating additional modalities, such as depth information or skeletal information, to improve the recognition accuracy. Real-time implementation: While the current systems are capable of recognizing hand gestures in images, real-time implementation remains a challenge, especially for resource-constrained devices.

Future research can focus on developing efficient and scalable implementations of hand gesture recognition systems for real-time applications. Extending to other sign languages: The results of the study are specific to Indian Sign Language, and the methods and techniques developed can be extended to other sign languages to improve the accessibility of sign language communication for the deaf and hard-of-hearing communities.

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