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Survey on Border Coolie Optimization Technique for Hand Gesture Recognition

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Abstract- Hand gestures are observed as an effective tool for making the interaction in the community with individuals having intellectual disabilities. It is highly essential for communicating the computers and people. Therefore, it is aimed to design an automatic hand gesture recognition approach that is utilized for repeatedly performing human-computer interaction. Sign languages are considered the natural languages utilized by hearing-impaired people that involve some expressional way of communication in routine life. It reveals the sentences, words, and letters present in the spoken language for performing the gesticulations that enable communication between them. The deaf community makes communicates with normal people using an automation system that relates the signs with the words of speech. The hand gesture recognition system is implemented independently of requiring any unique hardware rather than using the webcam. Thus, it is highly significant to make a short review of hand gesture recognition based on deep learning techniques considering the Indian sign language. Hence, this paper discusses and clarifies existing research work based on hand gesture recognition in Indian sign language with algorithmic classification. This survey also compares different performance measures, datasets utilized, and also different tools used for the implementation. Then, upcoming research and also current research gaps in hand gesture recognition in Indian sign language are analyzed. This review on state-of-the-art hand gesture recognition for Indian sign language tools has shown their potential for providing the right solution in different real-life situations. It is hoped that the contents and illustrations in this paper assist researchers in laying a good foundation to inform their studies.

Keywords- Hand Gesture Recognition; Indian Sign Languages; Deep Learning Techniques; Algorithmic Categorization; Performance Metrics; Dataset Details; Implementation Tools

I. INTRODUCTION

Hand gesture is termed basic and natural interaction and is also used as a communication tool for supporting human beings since it has been utilized to convey information before the arrival of language-based communication. Here, the continuous finger placements and hand movements convey the information through the hand gesture, which makes complex operations to be easier [1]. Thus, the hand gesture is employed as the more adaptive interface to perform Human-Computer Interaction (HCI), in which the interaction is modernized by removing physical contact between the users and mechanical devices. As a consequence, this makes the extreme renovation of HCI, and it dramatically transformed the HCI process along with the user experience when required for various useful applications [2]. Sign language recognition causes immediate and essential effects on most essential applications. The fundamental way of communicating with people having hearing loss or deafness is attained using hand gestures. Hand gesture-based communication is generally termed sign language. When sign language comes as a communication tool, many public is lacking in interpreting knowledge about hand gestures the sign language [3]. Consequently, the communication barrier causes and makes discomfort in communicating with the general public and minority groups. Hence, the development of recognizing the hand gesture is considered an essential part since it is employed for breaking down the communication barrier that permits the common public to interpret the sense of sign gestures effectively.

Generally, hand gesture recognition has been distinguished into two classes, static and dynamic hand gesture recognition. Static gesture recognition makes the classification of hand gestures from the images, and at the same time, dynamic gesture recognition performs video processing that has multiple frames for recognizing the hand gestures. Two significant techniques are considered for performing the static hand gesture recognition that is employed with the vision-based technique and wearable device-based technique [4]. The wearable device-based technique uses a broad range of wearable devices like electrical impedance tomography, electromyography, data glove, and Myo armband together with the support of a leap motion device for recording the information about the hand gesture. But, these wearable devices are commonly used for capturing highly accurate information, and the utilization of hand gesture recognition systems is essentially restricted since the signers are essential for wearing a similar device beforehand, which leads to inconvenience and cost inefficiency. Traditionally, dynamic hand gesture recognition systems utilize diverse approaches for extracting the handcrafted features based on the sequence modeling approach like Hidden Markov Model (HMM). Yet, the recent success of the deep learning approaches used in the areas of speech recognition, image classification, and human activity recognition [5] has influenced researchers for exploiting the deep learning application toward hand gesture recognition. Convolutional Neural Networks (CNN) have been broadly utilized to learn the visual features among computer vision applications. However, a 3D CNN technique has been utilized for video modeling that is considered an extension of the standard CNN techniques that are involved with the spatiotemporal filters. A highly essential features of the 3DCNN are the capability of directly generating the hierarchical representation of the spatiotemporal data. But, it needs a high amount of parameters when compared to 2DCNN, which is considered as the major disadvantage. Furthermore, 3DCNN contains a supplementary kernel dimension that makes complexity in training the network. By considering all these challenges in the deep learning techniques, it is decided to analyze most of the deep learning techniques used for hand gesture recognition, which may be helpful for future researchers.

The main contributions of this research work are displayed as follows.

- To make the short survey on the hand gesture recognition system based on various deep learning strategies that support future researchers to choose better deep learning techniques for recognizing hand gestures.
- To perform the algorithmic classification, dataset analysis, implementation tool evaluation, and performance measures used for the conventional hand gesture recognition models based on the deep learning concept.
- To provide the research gaps in the conventional studies of hand gesture recognition to influence the researchers to take correct decisions in developing an efficient hand gesture recognition model in the future study.

The remaining sections presented in the survey of hand gesture recognition models are described below. Section II provides the literature review of the conventional hand gesture recognition systems along with the dataset as well as implementation tool analysis and chronological review. Section III explains the algorithmic categorization and performance metrics analysis. Section IV describes the research gaps and challenges regarding hand gesture recognition. Section V concludes with the survey on hand gesture recognition.

II. LITERATURE REVIEW ON HAND GESTURE RECOGNITION

A. Related Works

Exiting works based on deep learning methods

In 2020, Hammadi et al. [6] developed a new dynamic hand gesture recognition system based on diverse deep learning techniques for feature recognition and globalization, global and local feature representations, and hand segmentation. The developed system was tested over the challenging dataset that comprised 40 dynamic hand gestures conducted over 40 subjects in an uncontrolled environment. The results have reported better efficiency of the proposed system over the conventional techniques.

In 2020, Aly and Aly [7] implemented a new framework for performing sign language identification under the signer-independent model based on diverse deep learning architectures, which were composed of hand semantic segmentation, and deep Recurrent Neural Network (RNN). The extraction of hand shape characteristics was attained through the efficient strategy based on the transfer learning concept. The continuously acquired features were attained through the Bi-directional Long Short-Term Memory (BiLSTM) for efficiently recognizing the hand gestures.

In 2020, Hammadi et al. [8] proposed an effective DCNN approach for identifying hand gestures. The developed technique has involved the transfer learning strategy to resolve the scarcity of a huge labeled dataset of hand gestures. The developed technique has a higher recognition rate on analyzing three datasets when considering the signer-dependent mode.

In 2021, Wong et al. [9] suggested an advanced and cost-efficient capacitive sensor device for determining hand gestures. Particularly, a prototype was implemented over the wearable capacitive sensor for acquiring the capacitance values through the electrodes, which were placed over the finger phalanges of the individuals. Further, K-Nearest Neighbor (KNN) was used for recognizing hand gestures. The recognition rates of the training and testing phases were considered, and it was observed to be higher for the developed model. In 2017, Oyedotun and Khashman [10] implemented a new deep learning mechanism for solving problems related to hand gesture recognition, in which deep learning technique like autoencoder was employed. This autoencoder could understand the complex hand gestures in the classification task with lower error rates.

In 2019, Skaria et al. [11] used a miniature radar sensor for capturing the Doppler signatures acquired from the 14 various hand gestures and also trained the DCNN. This technique was used for categorizing the captured gestures. With the utilization of two different receiving antennas belonging to continuous-wave Doppler radar, this has the capability of generating the quadrature and in-phase elements of the beat signals. These were used in the DCNN for identifying hand gestures.

In 2022, Bhaumik et al. [12] developed a lightweight Intensive Feature Extrication Deep Network (ExtriDeNet) for precisely recognizing hand gestures. This developed network was composed of two blocks, Intensive Feature Assimilation Block (IFAB) and Intensive Feature Fusion Block (IFFB). The combined multi-scaled filters influenced the network having the highly essential features that have improved the network interpretability. Hence, the developed ExtriDeNet has provided efficient performance with diverse features belonging to various hand gesture classes and also has attained better efficiency when compared to other conventional algorithms.

In 2018, Li et al. [15] presented an efficient deep attention technique for performing the joint localization and identification of hand gestures based on static RGB-D images. This developed technique has trained the CNN model according to the soft attention strategy that has enabled the automatic localization of hands and identification of gestures.

In 2020, Ameur et al. [17] developed a new architecture with the combination of various deep learning models along with the support of supplementary elements for providing final prediction architecture. This network was named Hybrid Bidirectional Unidirectional LSTM (HBU-LSTM). The developed architecture has enhanced the model efficiency with the consideration of temporal and spatial dependencies among the leap motion data and the network layers at the time of the backward and forward pass.

In 2019, Pinto et al. [19] proposed an efficient gesture identification approach based on CNN. The steps involved with the application of segmentation, polygonal approximation, contour generation, and morphological filters, which has benefits for enhanced feature extraction. Testing and training were conducted using diverse CNNs by comparing the developed architecture with other mechanisms.

In 2022, Hammadi et al. [20] presented an effective structure for recognizing sign language according to Graph Convolutional Network (GCN). The developed system has composed of several separable 3DGCN layers that were improved with the support of a spatial attention strategy. The restricted layers were utilized in the developed mod that has enabled avoiding the basic over-smoothing issue in the deep learning networks. Moreover, the attention mechanism has enhanced the spatial context representation of the gestures.

In 2019, Liao et al. [21] suggested a multimodal dynamic sign language identification technique using the ResNet mechanism. Initially, the hand objects were localized over the video frames for minimizing the space and time complexity of the network. Then, the extraction of spatiotemporal features was done from the video sequences, and the classification of the video sequence was made with the deep scheme and appropriately determined sign language.

In 2019, Mittal et al. [22] proposed a modified LSTM framework for analyzing the continuous gestures or sign languages that can identify the continuous gestures. It was performed by separating the continuous signs to generate the subunits and has been modeled with the help of neural networks.

In 2022, Prakash et al. [23] developed fine-tuned CNN framework for recognizing the gestures obtained from the standard datasets. This model was based on the score-level fusion approach for recognizing hand gestures by training with minimum gesture images.

In 2022, Subramanian et al. [24] implemented Media Pipe Optimized Gated Recurrent Unit (MOPGRU) architecture for recognizing the Indian sign language. This model has particularly enhanced the update gate present in the GRU architecture by integrating a reset gate for discarding unnecessary information from the previous sections.

Research works based on various methods

In 2020, Gangrade and Bharti [13] implemented a new algorithm for detecting and segmenting the hand region over the depth image based on the support of the Microsoft Kinect sensor. The developed technique has performed well under the consideration of a cluttered environment that was observed to be hand overlapping on the face and skin color background. CNN was involved in the automated designing of features through the Indian Sign Language (ISL) signs. In 2021, Kumar [14] utilized 3D-CNN for modeling the highly used gestures belonging to the Indian community. The trained framework has assured the natural language output respective to the signs belonging to ISL. This was also supportive of minimizing the problems that happened for dumb and deaf people.

In 2020, Lupinetti et al. [16] presented an efficient approach for recognizing the collection of non-static gestures obtained from the leap motion sensor. The obtained gesture information was transformed into color images, in which the hand joint position variations were shown at the time of doing the gesture, and also the temporal information was interpreted using the color intensity belonging to the shown points. The gestures were classified based on CNN, in which the advanced version of CNN named ResNet-50 was incorporated and also acquired with the removal of the last fully connected layer and also have combined a novel layer with various neurons into the given classes of gestures.

In 2020, Canuto et al. [18] developed a new approach having the capability to condense a dynamic gesture presented in the video over the RGB image. This image was further forwarded towards the classifier generated using ResNet-CNN, fully connected layer, and soft attention ensemble that have denoted the gesture classes of the input video.

In 2020, Imran and Raman [25] proposed an efficient framework for performing the automated sign language identification model independent of doing hand segmentation. The developed technique has initially produced three diverse kinds of motion templates such as developed RGB motion image, motion history image, and dynamic image. These images were utilized for identifying the hand gesture in the Fine-tuned CNN network.

B. Dataset analysis

Researchers have employed various datasets for hand gesture recognition systems in the existing research works that are depicted in Table I. The mostly utilized datasets for hand gesture recognition are observed to be ASL and ISL datasets. Rarely used datasets are presented in [10], [16], [17], and [21]. More datasets are used in [12] nearly five datasets are used for recognizing hand gestures.

TABLE I. DATA USED IN THE CONVENTIONAL HAND GESTURE MODELS

Citations	Dataset Name
[6]	King Saud University Saudi Sign Language (KSU-SSL) dataset
[7]	American sign language (ASL) dataset
[8]	KSU-SSL Dataset
[9]	ASL dataset
[10]	Thomas Moeslund's gesture recognition database
[11]	Manually Collected Gesture Dataset
[12]	MUGD, Finger Spelling, OU Hands, NUS, and HGR1
[13]	ISL dataset and NUS dataset-I
[14]	Indian Sign Language (ISL) dataset
[15]	NTU Hand Digits (NTU-HD) benchmark and HUST-ASL dataset
[16]	Leap Motion Dynamic Hand Gesture (LMDHG) database
[17]	LeapGestureDB dataset and RIT dataset
[18]	Montalbano gesture dataset, GRIT gesture dataset, and IsoGD gesture dataset
[19]	Self-acquired dataset of ASL
[20]	KSU-SSL Dataset
[21]	DEVISIGN_D dataset and SLR_Dataset
[22]	Sign Language Data
[23]	Massey University (MU) Dataset and HUST-ASL Dataset
[24]	Word Level American Sign Language (WLASL) dataset and LSA64 dataset
[25]	LSA64 Argentinean sign language dataset, SKIG dataset, DHA dataset, IITR Sign Language Thermal Dataset (ISLTD)

C. Chronological review

The year-wise analysis is made over the conventional hand gesture recognition systems that are considered for this survey. The chronological review on hand gesture recognition is shown in Fig. 1. It shows more contributions taken from the year 2020, and secondly, the years 2019 and 2022 took the same position in the graph, which shows an equal number of contributions. Low contributions were observed in the years 2017 and 2018.

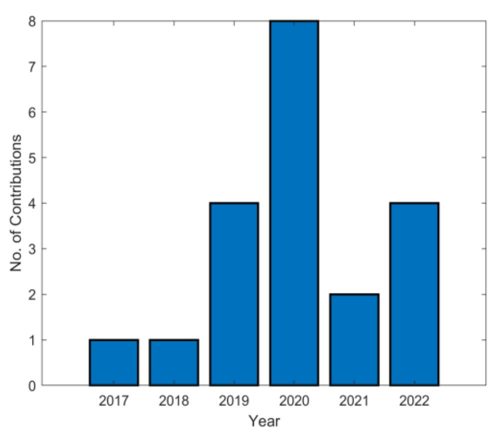

Fig. 1. Chronological Review of Hand Gesture Recognition

D. Study on implementation tools

The implementation platforms considered for this analysis that is used for developing conventional hand gesture recognition systems are graphically shown in Fig. 2. From this analysis, it is known that Python and NVIDIA are considered to be the most highly used implementation tools. The graph analysis shows a few recent existing works are explored based on various implementation tools for trends on Hand Gesture Recognition of Indian Sign Languages. Here, various implementation tools like K-fold cross-validation, Python, NVIDIA, MATLAB, Caffe, and miscellaneous tools were investigated. Consequently, the Python, and NVIDIA are utilized in 4 existing works. Other implementation tools like MATLAB, Caffe, and Cross-validation took the same position in the contributions. The second high tool is observed to be PyTorch.

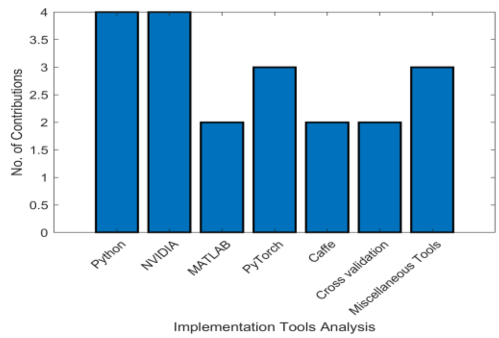

Fig. 2. Algorithmic Classification for Hand Gesture Recognition

Here, the deep learning techniques are classified into two classes, CNN-based techniques, LSTM-based techniques, and other deep learning techniques. Moreover, various deep learning and machine learning methods are used in the hand gesture recognition. But, the review has analyzed the CNN and LSTM methods due to their effective performance when compared with other existing methods.

CNN-based hand gesture recognition techniques [13] [15] [19]: CNN is a widely used deep learning approach because of its ability to automatically extract the features from the given images and provide a higher accuracy rate with minimal parameters. Some of the CNN techniques like 3DCNN [6] [8] [14], DCNN [11], ResNet-CNN [18], GCN [20], ResNet [16] [21], and Fine-Tuned CNN [23] are used in the conventional hand gesture recognition models. Some of the advantages of the CNN method are listed here. It can be utilized in larger datasets to provide excellent performance in hand gesture recognition. Moreover, it helps to speed up the training process in the network model. The complex feature extraction has been solved using the CNN model. Hence, it has a strong feature extraction and classification performance, which can be widely applied in various fields.

The ResNet and CNN are combined to perform effectively in the images of gesture recognition which helps to improve the spatial resolution. Hence, it is used to mitigate the gradient vanishing problem. Fine-Tuned CNN can utilize to provide a higher convergence rate. Hence, it provides the better outcomes in complex dynamic environments to recognize the hand gestures in the HBU-LSTM.

LSTM-based hand gesture recognition techniques: This network is used for gradient vanishing problems by selectively learning the information about the hand gestures. Several LSTM techniques, like BiLSTM [7], HBU-LSTM [17], and Modified LSTM [22], are utilized for performing hand gesture recognition. Moreover, the LSTM can be performed more accurately to recognize hand movements. Hence, it helps to solve the occlusion problem and the rotation invariant.

Other deep learning techniques used for hand gesture recognition are mentioned to be KNN [9], Autoencoders [10], ExtriDeNet [12], ResNet-50 [16], MOPGRU [24], and KELM [25].

The diagrammatic representation of the algorithmic classification for Hand Gesture Recognition Systems is given in Fig. 3.

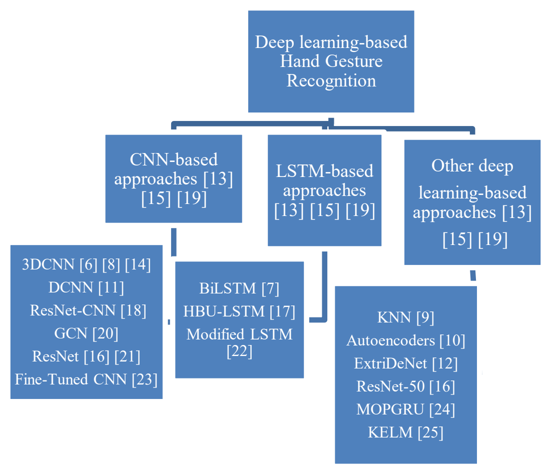

Fig. 3. Algorithmic Classification for Hand Gesture Recognition

B. Evaluation metrics on Hand Gesture Recognition Systems

The efficacy analysis is made to evaluate the performance of the developed hand gesture recognition system based on various performance metrics, as shown in Table II. This table analysis shows that the accuracy metric is used in all the existing models to confirm their recognition rate. A confusion matrix is also utilized by most conventional systems. Only three research works [9], [13], and [24] consider the error metrics like Mean Square Error (MSE), MAE, and overall error rate.

TABLE II. METRICS USED FOR PERFORMANCE VALIDATION OF CONVENTIONAL HAND GESTURE RECOGNITION MODELS

Citation	Accuracy	Precision	F1-score	Recall	Confusion Matrix	MSE	Miscellaneous
[6]	✓	-	-	-	✓	-	-
[7]	✓	-	-		✓	-	Mean Intersection-over-Union (MIoU)
[8]	✓	-	-	-	✓	-	-
[9]	✓	-	-	-	-	✓	Running time
[10]	✓	-	-	-	✓	-	-
[11]	✓	✓	✓	✓	-	-	-
[12]	✓	-	-	-	✓	-	-
[13]	✓	-	-	-	-	-	Error Rate, Prevalence, Sensitivity, Specificity
[14]	✓	✓	✓	✓	-	-	-
[15]	✓	-	-	-	-	-	Time Complexity
[16]	✓	-	-	-	✓	-	-
[17]	✓	-	-	-	✓	-	-
[18]	✓	✓	✓	✓	-	-	-
[19]	✓	✓	✓	✓	-	-	-
[20]	✓	-	-	-	-	-	-
[21]	✓	-	-	-	-	-	-
[22]	✓	-	-	-	-	-	-
[23]	✓	-	-	-	-	-	-
[24]	✓	-	-	-	-	✓	Mean Absolute Error (MAE) and R-squared Metrics
[25]	✓	-	-	-	✓	-	Computational Complexity

III.RESEARCH GAPS AND CHALLENGES

Hand gesture recognition is traditionally performed by the vision-based technique that is highly flexible and convenient since it provides better efficiency in the recognition rate of hand gestures. This technique needs only cameras for capturing the hand gesture image and is independent of requiring the signer to be worn with the specialized equipment. Hence, it is highly convenient and establishes the way of capturing hand gestures naturally, and this recognition system is developed without any restrictions towards the smaller space or scope. Even though it has various advantages, this vision-based technique also contains certain demerits. Various challenges are occurred due to the variations in viewpoints, hand sizes, and skin tones. Some other challenges, like background noises, varied illuminations, and gesture similarity over the collected images are, occurred in the recognition system. Here, the vision-based approach is classified into two types such as deep learning and hand-crafted approach. This handcrafted technique contains diverse stages of complex visual processing phases, and these approaches are used for solving various challenges in a specific manner, which makes it more complex for performing with multiple datasets and frequently acquires substandard generalization. Thus, the

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efficiency of the hand-crafted technique and its capacity to deal with diverse challenges among various datasets depends on the technique utilized. From this, it is observed that the hand-crafted approaches are limited since the images obtained from the natural environment are presented with varied conditions for hand gesture recognition.

Deep learning techniques are involved with supervised learning for solving various conventional challenges in hand-crafted approaches. CNN is a deep learning technique that is predominantly utilized for image recognition tasks that includes sign language recognition. CNN employs the backpropagation mechanism for tuning the trainable parameters over the network at the time of training to get the optimal weights that reduce the loss occurrence. This makes the CNN create essential features among diverse datasets, and thus, it can resolve the challenges of the conventional hand-crafted approach. However, it also has various challenges, and many researchers are developed various experiments for improving the conventional CNN components like normalization strategy, activation functions, and pooling operations in the various research works. Networks having various layers are affected by the gradient vanishing issue and also, and it requires a huge amount of training parameters. In addition, the residual network employs the shortcut association for reducing the gradients vanishing issue, and also, the research works are performed over the sequential operations in the residual blocks for further improving the generalization ability. Still, the residual network needs more amount of trainable parameters for hand gesture recognition. Thus, this short survey analyzes the conventional deep learning techniques used for hand gesture recognition based on their performance which supports future researchers to choose better deep learning techniques for recognizing hand gestures.

IV.CONCLUSION

This paper has surveyed the earlier developed hand gesture recognition models by considering diverse deep learning approaches with the Indian sign languages. The deep learning techniques have been classified and explained. In addition, this paper has concentrated on datasets utilized and implementation tools employed for conducting the experiments. In addition, the performance metrics utilized to evaluate the developed model have been considered for the analysis to showcase better metrics. Finally, the research gaps towards future direction were explained to encourage the researchers for making further developments in the hand gesture recognition models over Indian sign languages.

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