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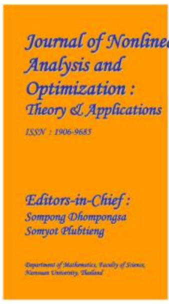

CONVOLUTION NEURAL NETS AND MOTIONS FOR RECOGNIZING TAMIL SIGN LANGUAGE IN INDIVIDUALS WITH DISABILITIES

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Abstract:
Outstanding scientific accomplishments in the field of deep learning-based gesture and hand sign identification have been endorsed by Tamil Sign Language. The behaviours that people with hearing impairments employ to communicate are referred to as "forms of communication". It is difficult for the average person to understand these behaviours. Due to differences in Tamil Sign Language (TmSL) within territories and then within states, the recognition of TmSL has become a challenging academic topic. The suggested approach, which is predicated on machine learning, incorporates the Convolution Neural Network. Utilizing the wearable sensor, Tamil Sign Language is recognized. This method makes use of an alternative mechanism that can accommodate all Tamil gestures. The research methodology has been applied with a fair degree of precision. Initially, a deep convolution network is created to extract features from the data collected by the sensing apparatus. The 30 hand sign letters used in Tamil sign language may be successfully recognized by these sensors. The DG5-V hand gloves with wearable sensors were used to record the hand movements in the dataset. The CNN approach is employed for the purpose of categorizing. The proposed system is designed to receive hand gestures used in Tamil sign language as input and produces vocalized speech as output. Ninety percent of the participants recognized the results.

Keywords: Tamil sign language; convolution neural network; Hand Movements; sensing device

INTRODUCTION

Globally, about 60 million people use body language; therefore, the impact of an automated body language interpretation tool on communication between users and non-users might be significant. Body parts are used in sign language, a wordless communication method. Face features, together with hand, eye, and lip gestures, are utilized to convey information in sign speaking and listening. Individuals who are hard of hearing or deaf primarily rely on sign language for everyday communication. Nevertheless, computer interpretation of hand signals was quite challenging due to the inconsistent size, shape, and posture of hands or fingers in an image. There are two ways to approach SLR: both image- and sensor-based. Expression frameworks' primary benefit is that they eliminate the need for consumers to use complex devices. In all cases, the pre-processing phase necessitates considerable activities. It is impossible to exaggerate the role language plays in development. In addition to acting as a conduit for interpersonal communication, it also helps with the internalization of social norms and the growth of communication control. Deaf children do not acquire a language to express themselves in the same manner as children with hearing impairments, despite the fact that they can hear the language spoken across them.

Recently, two categories of SLR research have been established: vision and contact-based methods. The interaction technique includes this sense-based relationship between devices and users. Usually, an interferometric glove is used, which uses electromagnetism, inertial estimation, or EMG signals to record finger motion, bending, movement, and angle information of the generated sign. The vision-based approach employs information from camera-captured pictures or video streams as the platform's input. Additionally, it is separated into two groups: 3D model-based approaches and presence . Most 3D model-based techniques start by assembling the hand's location and joint angle in three dimensions into a two-dimensional picture. While demeanor identification uses features taken from the PowerPoint display of the image, recognition is finished by matching the traits. Few "regular" individuals are able to understand or use sign language, despite the fact that many hearing-impaired people are proficient in it. People become less able to communicate with one other and with the "regular" society as a result of this. By implementing technology that continuously translates sign language to text and vice versa, this gap can be closed. Researchers have now been helped by numerous paradigm shifts in a wide range of scientific and technological domains to propose and put into practice sign language recognition systems. Instead of using spoken or written language, people with disabilities communicate by hand signals, which are gestures.

The deaf Tamil communities are a tightly-knit community. There is little interaction between the hearing and the deaf communities; instead, the deaf community concentrates on its members, their relatives, and occasionally professionals and playmates. A feature extraction technique for Tamil sign language and a continuous identification program based on the K-nearest neighbor classifier are used in the recognition process. The main drawback of Tubaiz's approach is that patients have to wear interferometric hand gloves in order to record particular actions, which can again be quite upsetting for users . An interferometric glove was developed in order to build an interpreter for Tamil sign language. Tamil sign language can be continuously identified using temporal characteristics and hidden Markov model (HMM) . An investigation of the conversion of Tamil sign language to text for use on mobile devices was conducted. While a variety of sign languages are covered in the aforementioned studies, Tamil Sign Language was also the focus of some research. For a sample of 300 words, the researchers obtain 93% accuracy using a Hidden Markov Model (HMM) quantifier. They employ KNN and Bayesian classifications, which yield comparable outcomes to HMM . This describes a network matching technique for continuously identifying sentences in Tamil Sign Language. The model makes use of decision trees and the division of motions into stationary postures. They translate multi-word sentences with at least 63% accuracy using a polynomial runtime method.

The study system used in this publication, which addresses gesture-based Tamil sign language recognition for people with impairments, is the convolution neural network approach. The Convolution Neural Network and Arab Sign Language processes are covered in separate sections. The Introduction of the Tamil gesture sign language and the machine learning system are provided in Section 1. In Section 2, the various approaches and studies related to Tamil language recognition were explained in detail; in Section 3, the suggested methodology is provided. In Section 4, the results and Discussion are examined, and the study is ultimately finished.

LITERATURE REVIEW

Hand signals are the most innovative and comfortable means of communication for the hard of hearing. Advances in multimedia tools and networks have always piqued the interest of academics in innovation. Systems for sign language communications can be used to improve network technology for those who are hard of hearing or speech, providing more social opportunities and inclusion. This paper presents a framework for using Tamil sign language to communicate with the Microsoft Kinect device. The gesture recognition architecture for Tamil signs put forth by for language communication systems serves as the foundation for the suggested approach. Experimental results show that the proposed Language for Arab sign technique has a 96% sign identification rate. Furthermore, an Tamil sign's average mission completion time was about 2.2 seconds. Consequently, the proposed technology can be applied to create an Tamil sign language communications network in real time.

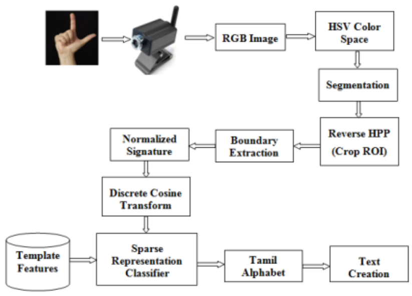
A survey was also conducted in the field of image processing, where optimization techniques are used to achieve optimal performance. In order to improve 2D and 3D posture estimates for object detection and classification in computer vision, Lee presented a geometric optimization approach. According to the experimental investigation, computer vision algorithms that successfully handle complicated issues are created using the geometric optimization approach . A dictionary tool for multilingual multimedia Indian Sign Language was created by Dasgupta et al. It was used to associate signs with the provided text. Based on the HamNoSys structure, the system created the phonological annotation of Indian signs. To create an animated sign depiction, the manually created HamNoSys string was sent into the avatar module . Johnson created a technique for recognizing Swedish sign language using visual cues. It concentrated on the segmentation of the hand region of the visual processing area in low light and complicated backdrop conditions. The skin tone model was built to extract characteristics that were then used to identify the gesture movement with the best level of precision.

Arab sign language recognition was suggested by the author Mr Kamruzzaman,, and sign language requires the movement of the hands and arms as a means of communication for people who are deaf or hard of hearing. The two main components of an automatic sign identification system are the recognition of specific traits and the categorization of particular input data. To increase dependability, a variety of classification and identification schemes for sign languages have been put out in the past. But recent developments in machine learning have encouraged us to look more into the use of deep neural networks for the recognition of hand gestures and signals. Considerable study has been done on hand gestures and gesture recognition using the Tamil gesture. This study suggests a vision-based system that converts Tamil hand sign letters into Tamil voice by using CNN. The proposed method uses a deep learning model to identify hand sign signals automatically and produces another output in Tamil. With 90% accuracy, this system can identify Tamil hand sign-based letters, demonstrating its high level of dependability. Accuracy can be further improved by utilizing more potent hand gesture detection technology, such as Motion Sensors or Xbox Kinect. The outcome will be fed into the speech engine along with the text, generating the audio for the Tamil hand sign-based characters.

METHODOLOGY

I. Tamil Sign Language Architecture

One suggestion for a low-cost multilingual translation tool is the Architecture for Tamil Sign Language Communication System. a communications network based on sign language, with excellent accuracy and cost-effective use The Tamil Sign Language Architecture is displayed. The three components that comprise the system architecture are the network, hardware, and software. The hardware device has a video representation and a gesture authentication method. A software component includes the digital storage repository for gesture recognition, the Sign recognition center, and the Sign media center. Data in Tamil sign language must be sent and received over a network connection by the network device.



. Fig. 1. Architecture of Tamil Sign Language

The hardware components of the system supply the transmitter and receiver channels that the user uses to control the device. The first generation Microsoft Kinect is used as the gesture input device; it gathers data and sends it to the sign recognition center . The audio system and digital display are the Display devices that show the output data from the Sign media center. Visual data is supported by the stability as it stands.

The software of the program is responsible for movement translation and feature extraction, in addition to providing a basic Graphical User Interface (GUI). The Sign Identification Center converts the raw input into an established set of predefined signs based on the current and established lexicon. The information regarding signs is retrieved from the Sign language data store. The signs that the Sign recognition center provides are translated by the Sign media center into the required language and medium, which it subsequently transmits to the display technologies or engages in conversation.

Both gesture dictionaries and translation dictionaries between different vernaculars are part of the gesture recognition data storage. Because the idea is still in the concept stage, certain things, such the information storage, have limited sizes.
Source: TmSL: Tamil Sign Language Alphabets Translator

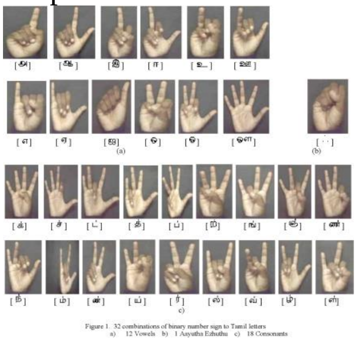


Fig. 2. Tamil Hand Sign.

Media is sent by the Signs media player to the Communication center, which forwards it to the appropriate location via the system. Since this area has nothing to do with usability testing, it is not currently implemented. The Tamil Sign Language Alphabets are displayed in Fig. 2 above; this picture may be utilized by the system for additional processing.

Preprocessing of Data

Preprocessing the data is the initial step in building a functional deep learning model. This is used to transform unprocessed data into an effective and useable format. Fig. 3 displays the data pre-processing flowchart.

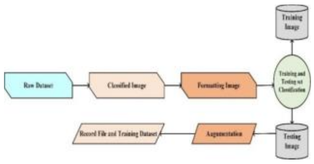


Fig. 3. Data Preprocessing.

Raw data: In this section, "raw data" refers to the image that was captured by the camera. An excellent illustration of the raw image is the Tamil hand sign image that is utilized in the recommended method. The following environments are considered while representing images:

- Varying angles.
- Variations in lighting conditions.
- Concentration and excellence.
- Modifying object size and distance.

Making raw photos is done with the intention of building a dataset for testing and training. the Tamil Alphabet from the program's recommended dataset.

Classified image: The Tamil Alphabet images are categorized using the approach that is described. In order to comprehend the system, photos from a single classification are kept in one subfolder. Within the established framework, a major special folder called "dataset" houses all subfolders describing categories.

***Number of epochs*:** The number of epochs indicates how many times the neural network is trained using the entire dataset. However, there isn't an ideal number; instead, it depends on the circumstances.

Image formatting: Hand sign drawings typically feature an uneven background. It is crucial to take out the unnecessary features from the pictures in order to acquire the hand component. Digital data that has been rasterized for use on a display device or printing is referred to as images in certain of those forms. The procedure of turning visual input into a set of pixels was applied to the extract.

Training and testing dataset classification: Using the training or testing image as a basis, the formatting image may be categorized. In a controlled learning approach to classification, the training data set is analyzed to determine the optimal correlations between two variables that will yield a robust predicting model. Developing a trained (fitted) model with good generalization to new, unidentified data is the aim.

Augmentation: Because real-time data is constantly changing (rotating, moving, etc.), it is always unreliable and incomplete. One way to raise the performance of deep neural networks is image augmentation. It makes a deliberate effort to alter images using rotation, shear, shifts, and flips. The proposed method utilizes this image improve raw pictures to dynamically rotate images from 0 to 360 degrees. Additionally, a tiny number of pictures were randomly torn along a 0.2-degree range, and a tiny number of them were horizontally inverted.

Figure 4, Convolution Layer, depicts the architecture for the CNN-based Tamil sign language recognition system. CNN is a machine learning (ML) system that implements its data collection activities using perceptron algorithms. We refer to these systems as artificial neural networks (ANN). The field in which CNN is most helpful is machine learning. It mostly helps in picture recognition and classification .The two components of CNN are classification and feature extraction. Every element has unique characteristics that need to be looked into. The ensuing sections will provide a detailed explanation of these components. One kind of neural network used to evaluate visual data is the convolution neural network (CNN, or ConvNet) . The importance of convolution layer nets in image processing is one of the primary reasons why academics have come to understand the effectiveness of deep learning. They oversee important developments in computer vision (CV), which has broad implications for safety, medical progress, unmanned aerial vehicle technology, self-driving cars, mechatronics, and vision impairment treatment. The architecture used by convolution neural networks is particularly well-suited for image classification. Neural nets can learn quickly thanks to these systems. This allows us to tackle improved deep multi-layer picture classification systems. CNN keeps employing the Backpropagation algorithm and its offshoots to learn from data. Specialized GPUs are used by modern implementations to further boost performance.

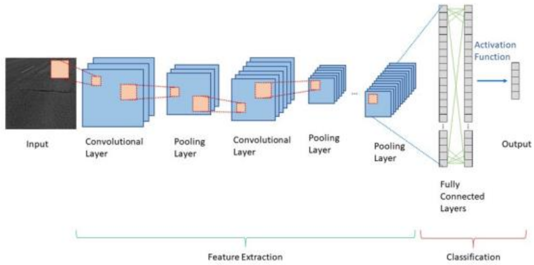


Fig. 4. Convolution Layer.

Input blocks: Squeeze Net needs an input block with three RGB channels that is at least 224 X 224 in size. CNN is composed of multiple parts. Conversely, the most crucial part of CNN is the convolution process. A convolution layer is a statistical combination of two roles that generates a third function. Filtering or kernel combination of the inputs is required to produce a feature map. To execute convolution, drag each filter over a designated input [24]. At each position, a matrix combination is executed, and the result is appended to a distinct feature map. Each image is converted to a three-dimensional matrix with predetermined depth, width, and height. Due to the image's (RGB). CNN is composed of multiple parts. Conversely, the most crucial part of CNN is the convolution process. A convolution layer is a statistical combination of two roles that generates a third function. Filtering or kernel combination of the inputs is required to produce a feature map. To execute convolution, drag each filter over a designated input [24]. At each position, a matrix combination is executed, and the result is appended to a distinct feature map. Each image is converted to a three-dimensional matrix with predetermined depth, width, and height. The image (RGB) displays the thickness as a measurement because it has colour channels.

Different feature extraction methods can be obtained by performing different convolutions on unprocessed data using different filters . The numerous feature photos are combined to form the convolution layer's output. After passing through an input layer, the output becomes complex. The stride is the amount of a given step that the Fourier filter takes each time. Usually, a step size of 1 signifies that the convolution filter is shifting an image pixel. Less cell overlap occurs when the step size is increased since the filters will move across the input more frequently. Because extracted feature is usually smaller than input size, researchers need take action to prevent it from diminishing. These will be used as a cushion in this instance.

$$Output_{size} = \frac{input_{size} - Filter_{size} + 2 * padding_{size}}{Stride_{\ size}}$$

Max pooling layer: A pooling layer is inherently created between Convolution layers. But its main objective is to use fewer parameters to reduce dimensionality and calculation time. It also reduces training time and avoids overtraining. Max pooling is the most common type of pooling, though there are other variations as well. It uses the highest value in every window, producing a feature map that is smaller but yet contains the same amount of data. Panel sizes need to be given in advance in order to predict the size of the output generated by the pooling layer; the following formulas can be used to do this.

$$Output_{size} = \frac{input_{size} - Filter_{size}}{Stride} + 1$$

No matter where a certain component appears on the panel, the pooling layer ensures that it is always recognized with a high degree of precision. The second most important part of CNN is the categorization component. A few interconnected layers make up the classification scheme for the items (FC). The neurons of an FC layer are strongly correlated with each activation of the layer that comes before it. The mapping of representations between inputs and outputs is facilitated by the FC layer. The same principles as a traditional neural network are used to perform the functions of the layer. Conversely, only an FC layer is able to take one-dimensional input. The novel method for reducing three-dimensional data to one-dimensional data uses Python’s flattening function.

Dropout regularization techniques: In deep neural networks, over fitting is a major and dangerous problem. Dropout is a strategy for overcoming this challenging obstacle. In order to do this, some neural units in the neural network with an artificially created ratio are randomly removed during training. There has been a significant decrease in the level of co-adaptation between neural units. Removing a thinned network from the original full network is the same as using dropout on a neural network. A number of thinning networks are gathered using dropout at a particular dropout ratio during the training phase. Combining the predictions from exponentially thinning models will not immediately aid in determining throughout the testing phase. This should forecast outcomes by implicitly aggregating the output of all systems, using an entire untinned network with less weight. Dropout performs better than other regularization techniques and significantly reduces overfitting. We would talk about the convolution neural network with dropout.

Activation function: A node positioned at the terminus of or amidst neural networks serves as the activation function. There are many other kinds of activation Compared to other training algorithms, ReLU has a major advantage in that it does not activate every neuron simultaneously. The above ReLU algorithm image demonstrates functions for this, but we'll focus on Rectified Linear Units (ReLU) in this talk. In neural networks, the goal function that is most frequently utilized is the ReLU function. that while it does not activate the neuron, it sets all negative input to zero. It is very computationally efficient because just a small number of neurons are activated at a time. In the positive domain, it doesn't get saturated. Compared to the sigmoid and $tanh$ activation functions, the ReLU activation function really converges six times faster.

Features extraction: There are various fundamental components that comprise the Convolution Neural Network. The CNN network's convolution layer is an essential part. The mathematical representation of functions that lead to a third function is indicated by this layer. Convolution must be carried out inside the input using a kernel or filter in order to produce a feature map. Convolution is implemented by sliding each filter with a enough amount of input. Matrix multiplication is done at each position, and the result is plotted on a feature map. A three-dimensional matrix with depth, height, and width is created from each image. Given that the image consists of color channels, depth has been classified as a dimension. The input dataset is subjected to many convolutions with suitable criteria, producing unique feature maps. The numerous feature maps are combined to produce the convolution layer's output. The kernel is an array of items in two dimensions (2D) that are typically employed as weights. The convolution process is carried out by dragging the kernel across the image, as shown in Fig. 5. The convolution layer's output is a mapping of features. Each section that is exposed to the convolution and dragging processes is known as an interested area (IR). The convolutional process is performed using the accompanying equation.

$$Z_{ij} = (I * K)_{ij} = \sum_{m} \sum_{n} I_{i-m,j-n} K_{mn} - 1$$

where I is the input picture and K is the kernel. The output of a convolution neural network for each layer is expressed as follows:

$$y_i^l = f(z_i^l)$$

$$\text{Then, } z_i^l = \sum_{j=1}^{l-1} w_i^j x_j^{l-1} - 2$$

In this example, y stands for the layer's outputs, z for the activation function, i for a layer-l neuron, w for weight, and x for
the input data.

$$w = \{w_{ij}^l : l = 1,3, \ldots L-1; i = 0,1, \ldots I; j = 0,1, \ldots J\} - 3$$

$$x = \{x_j^l : l = 1,3, \ldots L-1;\ j = 0,1, \ldots J\} - 4$$

The second layer of the CCN is the pooling layer. This layer's main objective is to simplify the feature mapping obtained from the convolution layer. By employing the maximum, sum, or average operations, it highlights the feature. The third layer is the fully connected layer. Converting a two-dimensional (2D) feature map into a one-dimensional (1D) one is the main purpose of this layer. When choosing a feature classification scheme based on pre-established features, this approach is suitable.

For this research, an Tamil sign language lexicon was used. used specific motions from a lexicon as a ground truth during the hand symbol identification training phase. The lexicon is presented as visual collections of motions. Each collection of pictures represents a distinct kind of social context. This selects more than 40 one-handed motions and more than ten two-handed actions. Convolution Neural Network training is done on this database. Coworker motions from real life were used to evaluate the device.

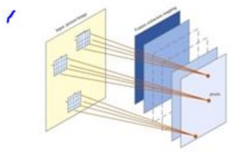


Fig. 5. Feature Extraction.

It took the creation of computer vision architecture to distinguish hands and fingers. It divides them and keeps an eye on them inside its field of vision. The architecture uses a collection of pixels to store movement monitoring data. The monitored data frames contain the measured locations, sign orientations, and other details about each object identified in the current frames. The recognized hands and fingers are depicted using a single, distinct pixel. Fig. 6 displays the CNN proposed model's flow chart. Use the following approaches to summarize a technique on still photos.

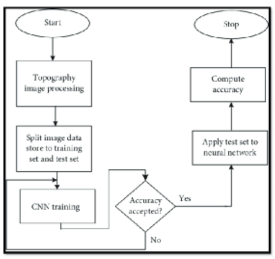


Fig. 6. Flow Chart for CNN Proposed Model.

• Using Convolution Neural Network (CNN) to distinguish a signer's face.

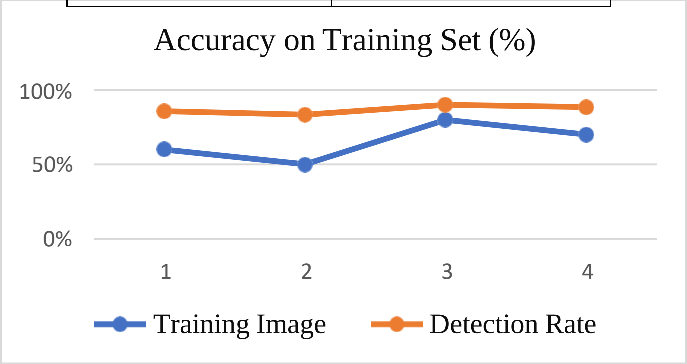
• Segmenting hand and finger motions with a convolutional neural network.
• Detecting motion with a convolution neural network.
• Motions can be identified by comparing them to elements in a pre-built database.
• Obtaining the translated text for the motion that was noted down.

RESULT AND DISCUSSION

To evaluate the proposed system, two convolution layers are employed. Two max-pooling layers come next to each completely connected layer. The convolution operation's first layer differs in pattern from the second level, which has 64 kernels, having 30 kernels in the first layer. Both layers have 3 × 3 layer kernels. We looked at two different dropout regularization values of 25% and 50% for each pair of convolution and max-pooling. This means that for every combination of convolution and pooling layers, one out of every four inputs (25%) and two out of every four inputs (50%) can be eliminated.
The different sizes of training sets, as shown in Fig. 7, allow the accuracy to reach its maximum of 90.03% when the network is trained using 80% of the dataset's photos. The Percentage Training Set is displayed in Table I. To illustrate the usefulness of the proposed system, researchers compared its results with those of KNN (k-nearest neighbor) with Euclidean distance and SVM (support vector machines) with different kernel processors often used in this field. Previous research have investigated other identification-influencing elements, such as facial motions. To manage the numerous characteristics mentioned above, several input detectors are integrated and different input detectors, such as the jump action controllers, are also used. Furthermore, a novel learning strategy was used in this investigation, and the results were promising.

TABLE I. PERCENTAGE TRAINING SET

Training Image	Detection Rate
60%	85.65%
50%	83.28%
80%	90.03%
70%	88.45%



. Fig. 7. Accuracy on Training Set

In the next phase (testing phase), the system then shows an optimistic accuracy rate with lower loss rates. When augmented graphics were employed, the accuracy rate decreased even more while keeping roughly the same precision. Prior to being utilized in this model, every digital image in the testing phase underwent processing. To represent the projected class value of the provided data, the suggested system creates a vector of 10 values, with 1/10 of these values being 1 and all other values being 0. After that, the system is connected to its signature stage, which translates a hand sign into Tamil speech.

CONCLUSION

Using a variety of symbols and signs together with Tamil Sign Language (TmSL), the identification of sign languages and TmSL were explored along with multiple categorization kinds and their outputs. The purpose of this suggested survey is to determine the optimal classifier for hand gesture recognition systems that utilize multiple sign languages. Only a few applications demonstrated the effectiveness of some of the developed models. In order to provide global coverage, the research come from all around the world and include a wide range of sign language variations. Neural networks, machine learning, and deep learning classifiers are some of the methods used to describe the complete process and performance of sign language recognition. The CNN classifier, which is based on deep learning, yielded the research results with respect to accuracy. Therefore, the Convolution Neural Network System serves as the foundation for the gesture-based Tamil Sign Language Recognition for Impaired People. Furthermore, in subsequent research endeavors, the extent of data collecting could be increased even further. Tamil-language speech is produced by the proposed method by identifying Tamil sign language. Moreover, the method put forth here would be fantastic for those with disabilities.

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