Advancing Communication: A CNN-Powered Framework for Assamese Sign Language Recognition

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Abstract: ***This paper introduces an advanced method for recognizing Assamese Sign Language (ASL) using deep learning, specifically Convolutional Neural Networks (CNN). The proposed framework encompasses three primary phases: data preparation, model development, and real-time gesture recognition. A dataset of 10 static gestures representing distinct Assamese alphabets was created, utilizing OpenCV for frame capture and MediaPipe for hand landmark detection. The collected data underwent preprocessing, and the hand gesture images were further split into training and testing sets. A CNN model was then trained for gesture classification, yielding a perfect accuracy score of 100%, along with exceptional precision, recall, and F1 scores across all 10 categories. The findings demonstrate the CNN model's proficiency in extracting and learning key features of ASL gestures, enabling the system to accurately recognize and convert the signs into text in real-time. This real-time recognition ability holds significant potential for enhancing communication between the deaf and hearing communities in Assam. Future work will focus on expanding the dataset to incorporate dynamic gestures and optimizing the system for real-time deployment in mobile applications.***

Keywords: Assamese Sign Language; Deep Learning; Convolutional Neural Networks; Gesture Recognition; Hand Landmark Detection

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1. Introduction

According to data from the June 2023 census, 63 million people in India, which accounts for roughly 6% of the country's total population, were reported to have auditory impairment. Additionally, over 1.5 million people worldwide had experienced hearing loss in the previous year. These individuals have developed their own form of communication known as sign language. These figures are based on research conducted by the World Health Organization (WHO) and other organizations. [1].

People with speech and hearing problems frequently utilize sign language, a visual gesture-based communication method, as their primary way of interacting with others. It is a form of visual communication that follows a set of grammatical and linguistic rules while using hand gestures and facial expressions to convey meaning.[2]

Sign language can be divided into primary and secondary components, which can then be combined either simultaneously or sequentially. The primary components are the positions of the body and hands, the movements of the hands and fingers, and the hand shapes that are used to create a sign. Many signs include body language and facial expressions along with hand movements. The hand is particularly important in sign language as it can convey most gestures. A gesture is a hand motion in the spoken language that forms words, sentences, alphabets, and numerals. These motions can be dynamic, involving varying hand movements, or static, involving constant hand positions with no variation in the hands' or fingers' positions over time. [3].

The usage of sign languages varies by location. American Sign Language is used in America, as opposed to Indian Sign Language, which is used in India. The Indian Sign Language Research and Training Center (ISLRTC) was founded to develop and standardize Indian Sign Language (ISL) after it was formally recognized in 2016 under the Rights of Persons with Disabilities Act. There are 33 different hand gestures used in the

ISL system, which include 10 numerical and 23 alphabetical representations. [4]. Out of the more than 19,000 languages spoken in India, 22 are modern, and Assamese is one of them. It is widely spoken in the state with 15 million native speakers. The deaf and dumb community in Assam extensively uses Assamese Sign Language, using hand signals to represent each of the Assamese alphabets.

Recently, methods for sign language recognition (SLR) have been created to aid in bridging the communication gap between the deaf and hearing cultures. Sign language recognition (SLR) is the process of converting sign languages into spoken or written language in computer vision. Two main approaches are used when developing SLR systems: vision-based techniques that use images or videos, and glove-based techniques that use data gloves. Each method has its own equipment, cost, and accuracy requirements [5]. In recent years, researchers have conducted many experiments to create systems that can recognize sign language (SLR). Studies on various sign languages have been carried out globally, but there has been relatively little focus on specific Indian dialects like Assamese. [6].

The goal of this research is to create a new system that can recognize Assamese Sign Language. In order to accomplish this, we will produce a customized dataset with 10 Assamese alphabets, referred to locally as Swaraborno (vowels) and Biyonjonborno (consonants), respectively. We have taken care to gather data on individual signs that can be combined to form meaningful two-letter Assamese phrases. Once the dataset is created, we will use machine learning techniques to identify and categorize these signs. Additionally, the system for recognizing Assamese sign language will be trained to recognize individual signs and combine them to form logical two-letter words.

2. Related Work

2.1 Indian sign language

J. Rekha *et al.* [7] had developed a method for recognizing Indian Sign Language by integrating shape, texture, and movement features of hand gestures, which significantly enhanced accuracy. Their approach proved effective in distinguishing similar signs, making it a valuable tool for sign language interpretation. S. Sharma *et al.* [8] developed a CNN-DSC model that reached accuracy rates of 92.43%, 88.01%, and 99.52% on three datasets. The model improved in robustness and performance through the use of data augmentation techniques, which helped it manage variations and scale changes effectively. In the work by K. Shenoy *et al.* [9], the system achieves 99.7% accuracy in classifying 33 ISL hand poses and 97.23% accuracy for 12 gestures. Utilizing techniques like object stabilization and skin colour extraction, alongside HMM and KNN models, it delivers precise real-time recognition with processing times of 0.2s for hand poses and 0.0037s for gestures.

2.2 American sign language

In the study by B. Sundar *et al.* [10], the vision-based system effectively recognizes Assamese Sign Language (ASL) alphabets and translates them into text using MediaPipe and LSTM models, achieving an accuracy of 99%. This system shows potential for human-computer interaction, allowing gestures to be translated into text for applications like typing or search engines, with possibilities for extension to real-time and multilettered recognition. T.W. Chong *et al.* [11] on 26 ASL letters and 10 digits, creating a sign language recognition system utilizing the Leap Motion Controller. Their study highlighted fingertip distance as a crucial feature, with the DNN classifier outperforming the SVM in terms of accuracy. Future research will investigate depth information, finger orientation, and extend the system to recognize words and sentences. A. Thongtawee *et al.* [12] proposed an innovative method for hand recognition by employing a 2D camera and relying on just four key parameters to derive features from hand images. Their system successfully classifies American Sign Language alphabet signs with impressive accuracy, though there are some minor errors added.

2.3 Regional sign language

M. N. Huda *et al.* [13] introduce a two-way communication system between Bangla Sign Language (BdSL) and Bangla, aiming to improve on previous limitations. While the system emphasizes real-time BdSL recognition, the conversion from Bangla to BdSL requires extensive datasets and grammatical structures that are not yet fully established. M. A. Hossen *et al.* [18] developed a DCNN-based framework to recognize Bengali Sign Language (BSL) using a dataset of 1,147 images covering 37 one-handed signs. The system attained an accuracy of 96.33% on the train data and 84.68% on the test data, showing strong performance across different conditions [18]. J. Bora *et al.* [6] introduced a real-time Assamese sign language recognition system. Their method, which uses a custom dataset and Feed Forward Neural Network, offers faster and more accurate classification of hand signs compared to traditional approaches. MediaPipe's hand tracking ensures precise gesture recognition and broad device compatibility, with future work planned to include more signs and dynamic gestures [6].

3. METHODOLOGY OF THE PROPOSED SYSTEM

3.1 Workflow

The proposed Assamese sign language system is implemented in 3 essential steps: data preparation, model building and training and real-time recognition.

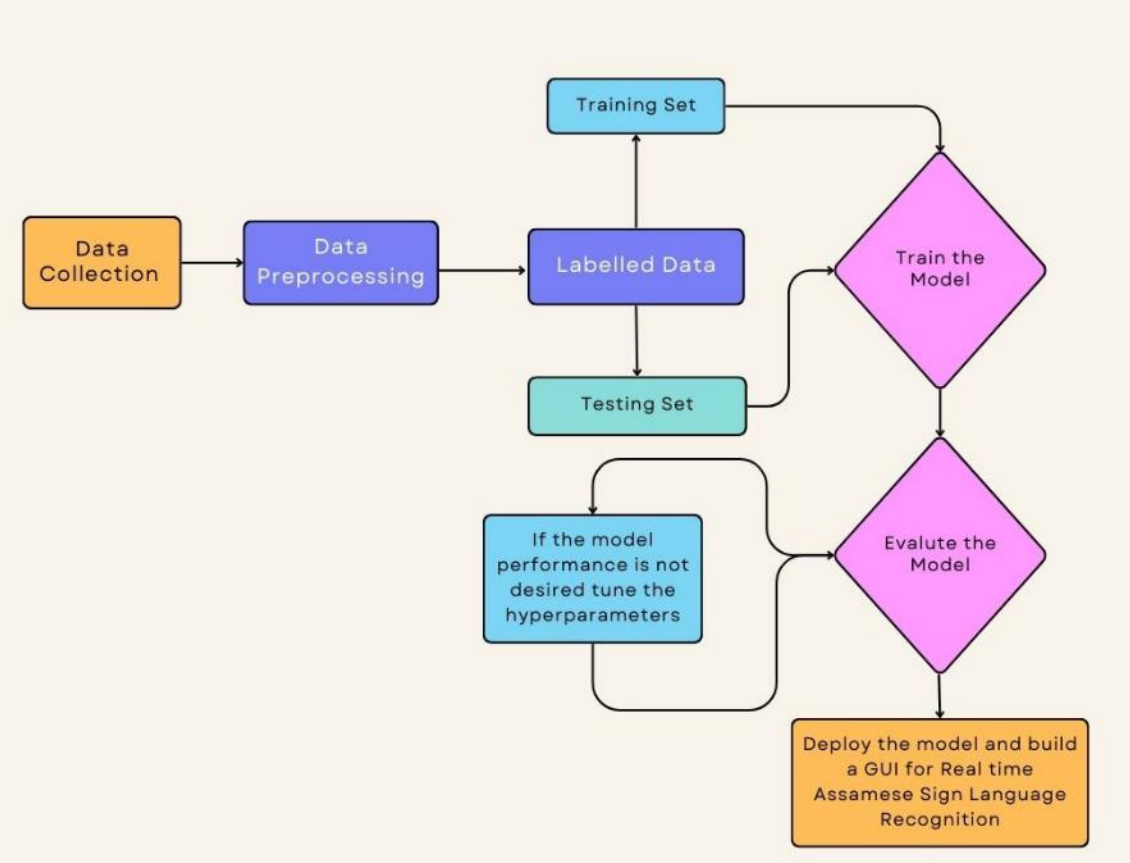


Figure 1: Workflow Diagram of the System

3.2 Data Collection

In the data collection process, we have prepared a dataset of 10 gestures of the Assamese sign language was created, which distinctly represented the Assamese alphabets. The 10 alphabets included **"অ", "আ", "ই", "ঈ", "উ", "ও", "এ", "ক", "জ", "ল".** These signs were originally developed by the Vaani® Foundations in 2021. The decision to include these 10 specific alphabets was made due to the fact that the proposed model is focused solely on the static gestures of Assamese sign language, excluding dynamic gestures. Moreover, static hand gesture recognition is simple, fast and more computationally effective making it ideal for basic sign language applications, alphabet and commands. The data for these signs was collected using OpenCV for capturing frames and processing, along with MediaPipe for landmark detection to accurately analyze hand gestures and movements. MediaPipe is an open-source library that helps us to enable real-time tracking of hand movements and locations. With 21 landmarks collected for each hand by the hand tracker module. Different variations of hand and background are used for the data collection as shown in the sample variation of each alphabet in Figure 2.

The entire process was carried out in the PyCharm environment to ensure efficient development and execution. With the required coding and enabling the webcam of the operating device, the images were captured which contained static hand gestures that included 7 out of 11 vowels and 3 out of 41 consonants of ASL. Once the data is collected, it is made into 10 classes and further labelling of the dataset is done. It has labels as: **"অ", "আ", "ই", "ঈ", "উ", "ও", "এ", "ক", "জ", "ল".** Each image of the dataset is of 128x128 pixel size. The whole dataset size is about 55.3 MB.

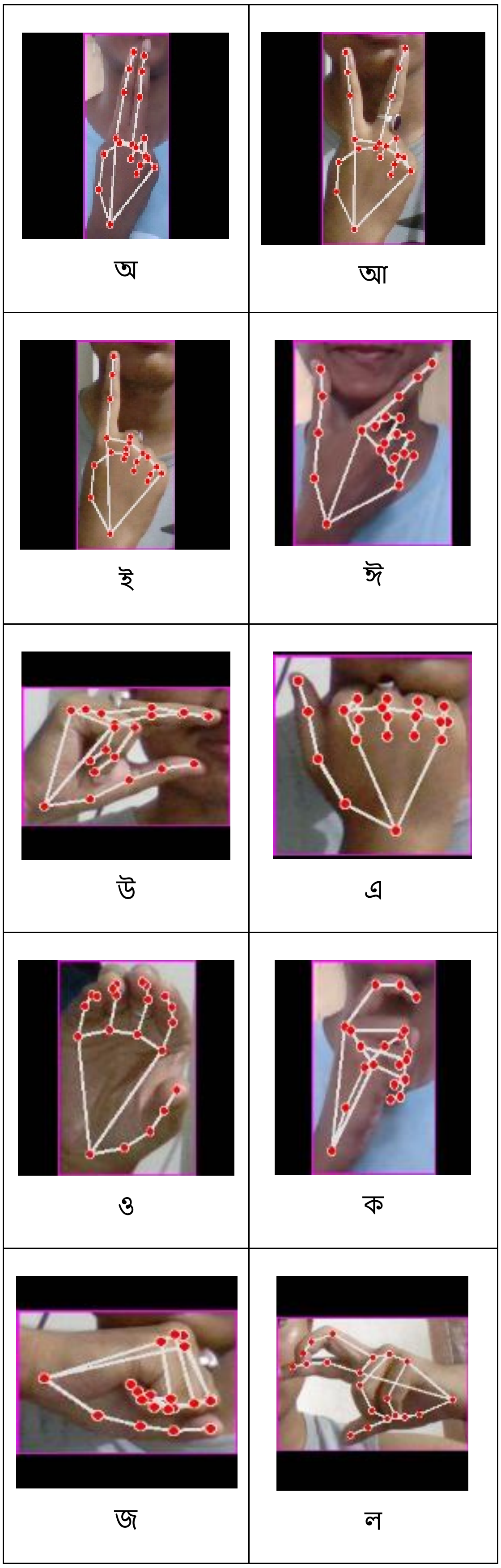


Figure 2: Sample frame of each alphabet

Data Augmentation is used in this system to improve model robustness and generalization. Image Data Generator is used for data augmentation in TensorFlow/Keras that helps augment the image in real-time during model training. The Table 1 shows the different data augmentation parameters used:

Table 1: Data Augmentation Parameters

Rescale	1./255
Shear Range	0.2
Zoom Range	0.2
Horizontal Flip	True

This research work has adopted the Stratified K fold cross validation to evaluate the performance across multiple splits. The Table 2 below shows the performance across multiple splits.

Table 2: Cross Validation Results

K-Value	Model	Accuracy	Precision	Recall	F1-Score
5	CNN	1.00	1.00	1.00	1.00
10	CNN	0.98	0.97	0.98	0.98

Table 3: Overview of Dataset

Class	**Total Dataset per class**	**Training dataset**	**Testing dataset**
অ	800	640	160
আ	800	640	160
ই	800	640	160
ঈ	800	640	160
উ	800	640	160
এ	800	640	160
ও	800	640	160
ক	800	640	160
জ	800	640	160
ল	800	640	160
Total	8000	6400	1600

3.3 CNN Architecture

A Convolutional Neural Network (CNN) consists of several layers, including convolutional layers, max-pooling layers, and fully connected dense layers. CNNs' architecture draws inspiration from the way the human brain processes visual information, and they work well for identifying spatial connections and hierarchical patterns in images.

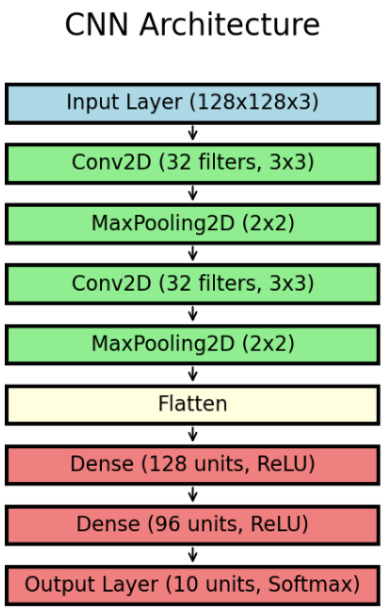


Figure 3: CNN Model Architecture

3.4 Feature Learning

Finding and removing important features from input data, such as pictures, is the goal of feature learning. Several layers make up CNN models, which are essential for feature extraction. To accomplish its goals, this approach makes use of a CNN architecture that consists of an input layer, two convolutional layers, and max-pooling layers for each. Raw photos that are represented as matrices of pixel values are processed by the input layer. By using convolution operations to find patterns such as edges, textures, or forms, convolutional layers use filters (kernels) to extract features. In particular, this procedure makes use of 32 filters with a 3x3 kernel size. The "ReLU" activation function, which adds non-linearity and allows the model to learn and represent intricate input patterns, is used in the convolutional layers. The purpose of padding is to maintain the spatial dimensions.

3.5 Model Configuration and Hyperparameter Settings

This method makes use of a 2D CNN model. To maximize model performance and reduce loss, a number of tests were carried out using different hyperparameter combinations. While Table 5 lists the many hyperparameter settings used during model development, Table 4 gives a summary of the model's configuration. Certain parameters, such as the Adam optimizer's learning rate of 0.001, were kept at their typical values. Furthermore, the training procedure was conducted over ten epochs, and the completely connected layers had 128, 96, and 10 neurons, respectively.

Table 4: Model Configuration

Layer	Output Shape
Conv 2D	(None, 128, 128, 32)
Maxpooling 2D	(None, 64, 64, 32)
Conv 2D	(None, 64, 64, 32)
Maxpooling 2D	(None, 32, 32, 32)
Flatten	(None, 32768)
Dense	(None, 128)
Dense	(None, 96)
Dense	(None, 10)

Table 5: Hyper Parameter Setting

Epochs	10
Batch Size	128
Learning Size	0.001
Activation Function	ReLu
Optimizer	Adam
Loss Function	Categorical Cross Entropy
Padding	Same

3.6 Challenges and Potential Solutions

The system encountered limitations when displaying non-ASCII labels such as ("অ", "আ", "ই", "ঈ", "উ", "ও", "এ", "ক", "জ", "ল".) due to lack of support for non- ASCII characters in OpenCV. OpenCV only supports three types of fonts Hershey Font, True Font, and Custom Font. To resolve this issue, this approach utilizes the "Noto Sans Bengali Font" from Google as it's compatible with OpenCV and supports Unicode, ensuring accurate rendering of Bengali characters.

4. Results

This section displays the results of the proposed system, assessed using crucial bracket criteria delicacy, perfection, recall, and F1 score. Delicacy reflects the model's overall correctness, while perfection measures the delicacy of prognosticated cons. Recall indicates the model's capability to rightly identify positive cases. The F1 score is a metric that harmonizes precision and recall into one value, providing a balanced measure of a model's performance, especially when there is an uneven class distribution. Formulas for these metrics are provided, representing true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), respectively. The classification report and confusion matrix from scikit-learn is used for comprehensive analysis. The classification report, which outlines the CNN model's performance metrics like Precision, recall and F-measure, is provided in Table 6. The heat map correlation matrix evaluates the performance of our proposed model. It displays the true labels on the y-axis and the predicted labels on the x-axis respectively.

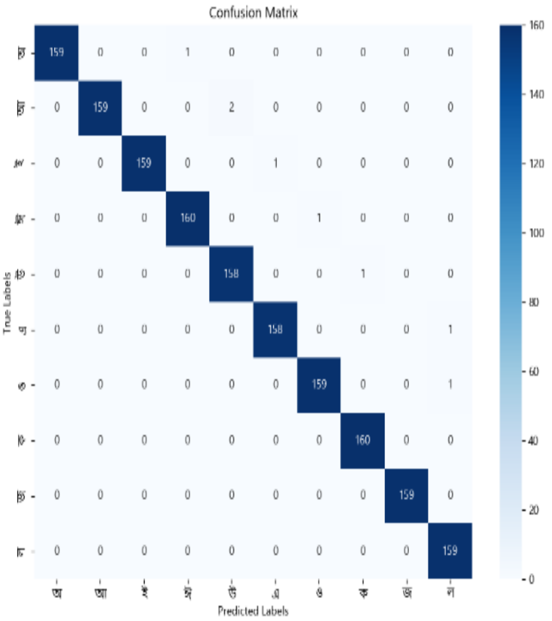


Figure 4: Heat Map Correlation Matrix

Table 6: Classification Report

Classes	Precision	Recall	F1 Score
অ	1.00	0.99	1.00
আ	0.99	0.99	1.00
ই	0.99	0.99	1.00
ঈ	1.00	1.00	1.00
উ	0.99	0.98	1.00
এ	1.00	0.98	1.00
ও	0.99	0.98	1.00
ক	1.00	1.00	1.00
জ	1.00	0.99	1.00
ল	1.00	0.99	0.99
Accuracy			1.00
Micro Avg	1.00	1.00	1.00
Macro Avg	1.00	1.00	1.00

The suggested CNN model with the parameters listed in Tables 4 and 5 provided us with a 100% accuracy rate, according to the results of multiple experiments with various settings. Figure 5 shows the loss score and the suggested CNN model's average validation accuracy. In Figure 5(a) and Figure 5(b), respectively, the x-axis displays the number of training iterations, while the y-axis displays the accuracy % and loss score. Figure 5(a)'s average learning curve demonstrates a consistent rise in accuracy percentage as training increases, suggesting that models are effectively learning from data. The total number of errors predicted by the model is known as the loss score. As seen in Fig. 5(b), the errors are instantly decreasing.

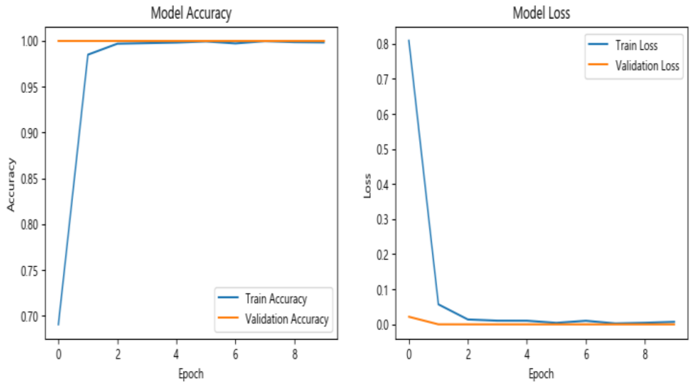
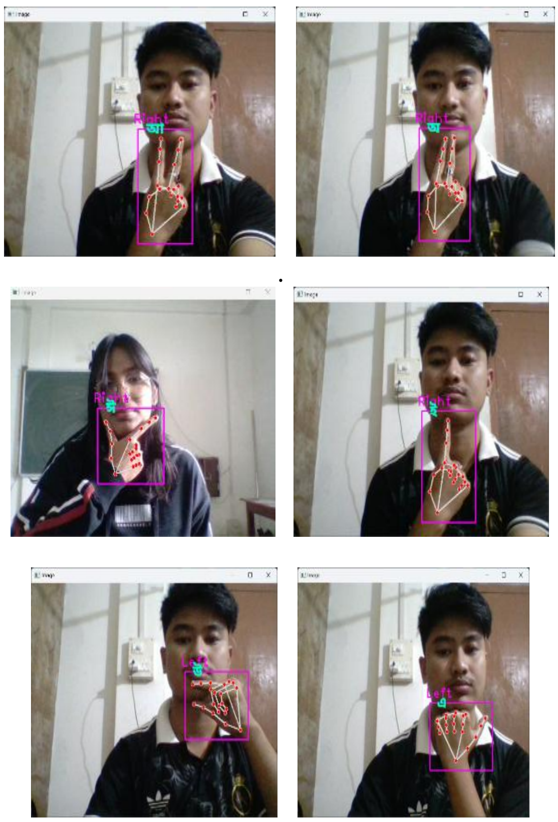


Figure 5: a) Training and Validation Accuracy
b) Training and Validation Loss

Figure 6 below shows the snapshots of the real-time recognition process. The result illustrates that the developed Assamese sign system successfully and accurately identifies gestures from language and converts them into text efficiently.

To reduce mistakes and avoid confusion during communication the system uses a confidence level to check the prediction. If the confidence is too low it ignores the prediction and marks it as unable to recognize.



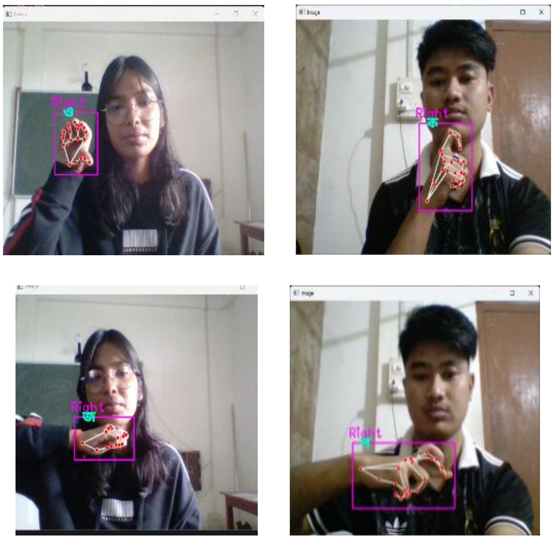


Figure 6: Snapshot of Real-Time Recognition of Assamese alphabets

4.1 Comparative Analysis

Table 7 provides a comparison of the results obtained in this study with those from previous literature on sign language recognition.

Table 7: Comparison to previous Sign language recognition System

Sign Language	Authors	Approach	Accuracy
Indian Sign Language	C. M. Sharma *et al.* [14], (2021)	CNN	100%
Bangla Sign Language	M. J. Hasan *et al.* [15], (2022)	CNN + KNN + SVM	95% (CNN Model)
Assamese Sign Language	J. Bora *et al.* [6], (2023)	CNN	99%
Bangla Sign Language	S. Das *et al.* [16], (2023)	CNN + Random Forest	91.67%
Indian Sign Language	V. Sharma *et al.* [2], (2024)	TCN	99.6%
Assamese Sign Language (10 Alphabets)	Proposed approach (2025)	CNN	100%

5. Conclusion and Future Scope

In this research, a comprehensive approach for recognizing Assamese Sign Language (ASL) has been enhanced using advanced machine learning techniques, specifically deep learning techniques. Our objective was to improve the communication gap between the deaf and the normal hearing communities in Assam, focusing on a dataset of ten distinct Assamese alphabets.

The journey began with meticulous data preparation, which involved collecting and preprocessing static hand gesture images. A CNN model has been designed and trained it specifically for recognizing ASL signs. The results showed that CNNs could effectively learn the unique features of ASL gestures, achieving impressive accuracy rates. By leveraging tools like OpenCV and MediaPipe, we were able to capture precise hand movements, ensuring our dataset was both reliable and rich.

The potential impact of this proposed model is significant. It could facilitate real-time recognition of signs, enabling smoother communication and even the formation of two-letter words. This advancement would greatly enhance interactions for users, making everyday conversations more accessible.

However, while these results are promising, authors recognize that there is still much work to be done. Future research could expand the dataset to include more signs and dynamic gestures, which would make the system even more robust. Additionally, exploring integration with real-time video processing and mobile applications could further support practical ASL recognition in daily life. Ultimately, our research is about more than just technology; it's about empowering the Assamese deaf community by providing tools for better communication. This initiative aligns with broader efforts to promote inclusivity and accessibility for individuals with hearing impairments, fostering a more connected and understanding society.

This study can be enhanced by including more dynamic action signs from Assamese Sign Language. Additionally, the application could be updated to generate sentences using dynamic Assamese alphabets, making it easier to teach the language to the hard-of-hearing community. There's also the potential to share the developed dataset publicly to support future research in this area.

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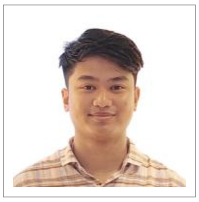
Authors' Profiles



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