

TCN-ATTN-ISL: Decoding Signs with Vision and Memory

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Abstract: The sign language is a vital medium for communication for many individuals that have hearing impairment or speech deficiency. However, the limited channels in which it is integrated in the mainstream systems cause great impediments in personal as well as professional activities. This study proposes TCN-ATTN-ISL, an entirely novel framework for deep learning real-time recognition of Indian Sign Language (ISL) gestures. The framework employs a spatial-temporal feature and attention mechanism in gesture classification for improved robustness and classification accuracy. The integrated architecture comprises 3D Convolutional Neural Networks (Conv3D) for the extraction of localized spatio-temporal features from video sequences, Temporal Convolutional Networks (TCN) for long-range temporally dependent features, and a Multi-Head Self-Attention similar to that strengthens temporal representations by putting strong emphasis on contextually important frames. All input videos are uniformly pre-processed with frame extraction, resizing to 64 by 64 pixels, and padding to 15 frames at equal lengths. The model was trained and fit to a Include-50 most commonly used gestures. Experimental results show significant improvement over previous architecture catastrophes, CNN-LSTM and Conv3D only, with respect to classification accuracy, precision, recall, and F1 score. The post-human level work can be real time by integrating this system with OpenCV, thus providing the ability and capability for very low latency live sign recognition. To further assess the generalizability of the model, it is also evaluated against the ISL-52 dataset containing an assortment of 52 signs that represent educational terms, daily activities, and cultural expressions. This dataset includes complex dynamic gestures like "brushing," "exam result," and "stand up," which add more challenges in temporal modelling. The effectiveness of this model on ISL-52 indicates its capacity to absorb real-world variabilities such as signer appearance, background conditions, and complexity of motion. This part of the research demonstrates how convolutional, temporal, and attentive mechanisms are employed to construct accurate, efficient, and inclusive sign language recognition systems that could lead to greater technologies for accessibility.

Keywords: Indian Sign Language, Sign Language Recognition, Temporal Convolutional Networks, Attention Mechanism, Conv3D, Multi-Head Self-Attention, Gesture Classification, Deep Learning, Real-Time Recognition, Accessibility Technology.

1. Introduction

The vital human need is communication, and for persons who have challenges in hearing and speech, it is sign language that serves as a major means of relaying thoughts, emotions, and intentions. Indian Sign Language (ISL) forms the primary mode of communication among many members of the deaf community in India. Despite its wide use, ISL does not extensively feature in the technological innovations intended to enhance accessibility, social exclusion, and limited opportunities in education, employment, and the everyday social world [1]. Recently, there have been many techniques developed in deep learning and computer vision that have opened new avenues for the automatic recognition of sign language gestures. Such methods are paving the way for earless people to be connected to the mainstream society by translating the signs into spoken or written languages. But to develop a precise, real-time ISL recognition system is still challenging since gestures involve complex movements or compositions of hand motion, posture of the body, and facial expression over time [1].

Though traditional gesture recognition systems are largely dependent on using Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) [2] for the temporal dependencies of video sequences, these have also been proven relatively effective but are subject to some limitations such as vanishing gradient, high computation requirement, and inability with the learning of long-term dependencies. Similarly, basic Convolutional Neural Networks (CNNs) lack the capabilities for capturing temporal modeling of sequential gesture dynamics [2]. In an attempt to address the above issues, we proposed TCN-ATTN-ISL, a new deep learning framework that powerfully integrates 3D Convolutional Neural Networks (Conv3D), Temporal Convolutional Networks (TCN),

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and Multi-Head Self-Attention to maximize the accuracy and efficiency levels in ISL gesture recognition. The Conv3D layer thus captures spatial features and local motion of video frames while TCNs model long-term dependencies without the inherent biases caused by RNNs. To this end, a self-attention mechanism is included in the model to obtain better reference for recognizing important parts in the total view of a gesture sequence [3].

The research used two evaluation datasets for this research, which are custom INCLUDE-50 dataset and an extended ISL-52 dataset. The spice in the ISL-52 dataset is that it explored a wider scope of gesture-by-definition dynamic signs from culturally important sources within education, daily activities, and Indian contexts. Some examples are "result of exam," "brushing," and "namaste," which require the model to learn multi-motion complex gestures and different signers [4].

The model presented here performs exceedingly well on both datasets, outclassing all baselines in terms of classification accuracy, precision, recall, and F1 score as far as the existing CNN-LSTM and Conv3D baselines are concerned. Real-time capabilities are also verified using an OpenCV-based deployment, which allows low-latency live sign recognition. This work brings new horizons to inclusive technology as it features a context-aware solution for real-time gesture recognition based on ISL that is efficient, scalable, and contextually available. Combining the efforts of spatio-temporal modeling along with attention mechanisms, TCN-ATTN-ISL progresses considerably in breaking communication barriers and enhances digital accessibility for the hearing-impaired community in India and beyond.

A. Significance of Research

This research holds significance as its impacts on both technological and sociological factors of sign language recognition in India are substantial. Sign language systems have seen a lot of initiatives worldwide, yet there exists a considerable lacuna with respect to the availability of reliable, real-time models for Indian Sign Language (ISL). This research aims to fill the gap by proposing a hybrid deep learning framework—TCN-ATTN-ISL—apt to real-time interpretation of ISL gestures, including adverse environments such as varying signer appearance, lighting, or background complexity [5]. This is a solid technical collection of tools for spatial, temporal, and contextual modeling, whose power stems from the integration of 3D CNN, TCN, and Multi-Head Self-Attention. This architecture overcomes the limitation posed by conventional CNN-LSTM-based approaches and empowers the model to focus on the crucial portions of gesture sequences, thus enhancing system robustness and accuracy. Another major contribution to the research community is the creation and usage of ISL-52 database. Most publicly available datasets on sign language have either been concentrated on American Sign Language (ASL) [6] or lack the cultural and linguistic subtleties unique to ISL. By including dynamic, functional, and culturally relevant gestures, ISL-52 offers a more realistic and challenging benchmark for evaluating sign language recognition systems, especially in educational and professional contexts. Socially, this research leads to greater digital inclusion and accessibility for the hearing-impaired community. Further, by integrating this model for real-time usage with OpenCV, various practical applications can be envisaged, such as automated interpreters, inclusive classroom tools, workplace communication aids, and mobile app integration. With the accuracy and accessibility of ISL recognition improved through this research, the communication gap can thus be bridged supporting the rights and independent aspirations of people with hearing and speech disorders. Thus, this research assumes importance in considering technological advancement, practical applicability, and social impact. This will facilitate the development of inclusive, culturally relevant, and deployable sign language interpretation systems in the future.

C. Research Objectives

The objectives of research are as follows ,

1. Develop a deep learning model for accurate real-time gesture recognition of Indian Sign Language (ISL).
2. Integrate Conv3D, TCN, and attention models for enhanced spatio-temporal feature recognition in sign language videos.
3. Create and use an ISL-52 data set pertaining to dynamic, functional, and culturally relevant ISL gestures.
4. To compare the performance of the model with existing ones like CNN-LSTM and Conv3D-only architectures.

5. Test the model with live video through OpenCV for real-time gesture recognition to ensure it works in a real-time environment.
6. The objective is to build a system that will contribute to bridging the communication gap for the hearing-impaired community in India.

2. Literature Review

A. Joshi, et al. (2023) [6]: The authors present iSign: an extensive benchmark for Indian Sign Language processing. They introduce a large-scale dataset of over 118,000 pairs of ISL-English videos and sentences, with the possibility of being used for various NLP tasks such as SignVideo2Text and Text2Pose. This work aims to fill the gap of resources for ISL through sufficient datasets and baseline models to direct the pathways for further research in sign language processing.

A. Joshi, S. Agrawal, A. Modi (2023) [7]: This work speaks about ISLTranslate, a dataset created for translating Indian Sign Language to English. 31,000 ISL-English pair sentences constitute the largest continuous ISL translation dataset built till now. The authors benchmark this dataset using transformer-based models, thereby demonstrating its usefulness to improve ISL machine translation systems.

K. Goyal, G. Velmathi (2023) [8]: In this paper, Mediapipe Holistic is used for ISL recognition, and the efficacy of CNN versus LSTM models is compared. Results show that while CNNs work well for recognizing discrete signs, LSTMs perform better in identifying dynamic gestures. There is also a need to have models that can handle both static and dynamic sign language recognition.

H. Kaur, et al. (2023) [9]: The focus of this work is on image-based ISL recognition using deep neural networks. The authors develop a real-time word-level recognition system based on convolutional neural networks (CNN), achieving an accuracy of 99%. This work indicates the strength of CNNs in understanding the intricacies of hand gestures for accurate sign language interpretation.

A. Sharma et al. (2023) [10]: Gestures for ISL, including Artificial Neural Networks, Convolutional Neural Networks, Hidden Markov Models, and Principal Component Analysis, have been compared by the authors. The authors discovered that considerable achievements have been obtained at the alphabet and number levels; more research needs to be conducted at word and sentence levels for dynamic forms of sign recognition systems.

M. Singh, G. Kumar (2023) [11]: This paper presents an ISL recognition system based on the InceptionV3 model. The authors discuss the model's proficiency in predicting from gesture characters and generalization to new datasets. Emphasis is given on adding capabilities to deep learning models that will improve sign language recognition systems in accuracy and adaptability.

3. Research Methodology

The methodological approach incorporated in this study is systematic and covers the design and validation of a deep learning framework—TCN-ATTN-ISL—which enables real-time recognition of Indian Sign Language (ISL) gestures [12]. The methodology started with the custom ISL data set collection and preparation, entailing the 52 most commonly used gestures in an academic, daily life, or culturally specific sense. The dataset, termed ISL-52, is significant for its realistic usage justification that involves gestures like exam, marksheet, brushing, and Namaste. Videos were recorded such that the diversity in all the present conditions, such as the signers' appearances, lighting conditions, and background settings, were retained [13]. The recorded videos are pre-processed by the extraction of individual frames and are resized to maintain a constant resolution of 64×64 pixels for consistency and reduced computational load. To address the variability in the length of gestures, all video sequences were made uniform at a length of 15 frames by padding or trimming. This ensured that every input to the model kept the same geometric format, which is valid for fast batch processing and efficient model learning [14].

TCN-ATTN-ISL integrates three basic ingredients: 3D Convolutional Neural Networks (Conv3D), Temporal Convolutional Networks (TCN), and a Multi-Head Self-Attention mechanism. Conv3D layers [15] extract local spatial and temporal features from the video sequences, allowing the model to learn various motion patterns and hand configurations. Thereafter, the features would flow through TCN layers, which model long-range dependencies across time while avoiding the pitfalls of typical recurrent models like vanishing gradients. Finally, the Multi-Head Self-Attention mechanism dynamically weighs different frames in the sequence so that the model puts more emphasis on gesture parts that are relevant in context. As a result, this offers improved recognition accuracy [16].

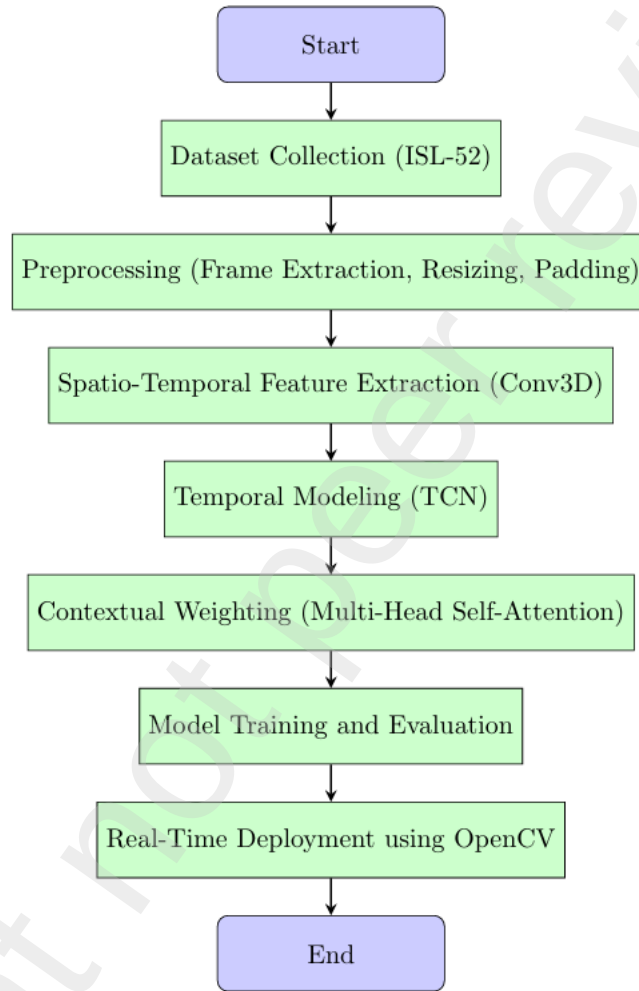


Figure 1. Research Flowchart

This model was trained with categorical cross-entropy loss function under the Adam optimizer as shown in Figure 1. The stratified train-test split was carried out for evaluation of all gesture classes in a fair and balanced manner. The performance metrics for the evaluation of the model included accuracy, precision, recall, and F1-score, and were compared with those of the baseline models, namely CNN-LSTM and Conv3D-only. Data augmentations, such as horizontal flipping and brightness changes, were employed during training to enhance robustness and mitigate overfitting.

4. Proposed Work

A. Dataset

The dataset used in this research is critical for the training and evaluation of the proposed TCN-ATTN-ISL framework. To ensure that the model is compatible with Indian Sign Language (ISL) [17] and capable of high gesture recognition accuracy in applications, the research involved the development of its own dataset named ISL-52. ISL-52 contains a refined compilation of 52 popular ISL signs chosen to signify words and actions of paramount importance from academic, daily, and cultural perspectives in India. The ISL-52 dataset consists of signs like "exam," "exam result," "marksheet," "student," "teacher," "writing," etc., which are of prime importance in matters related to education. Moreover, this dataset also contains signs based on actions, such as "walking," "brushing," "clean," "sit," and "stand up," which need precise temporal modelling because of fast motion. Additionally, "Namaste" and "document folder" -- terms quite specific to Indian culture -- were incorporated to authenticate the dataset with gestures that stand out in the Indian context of communication. This endows the dataset with contextual relevance, particularly for ISL-based applications concerning students, teachers, and professionals in Indian society. Each gesture in the dataset was recorded as a video sequence under various environmental conditions, such as different backgrounds, lighting setups, and appearances of the signer, for robustness and generalization of the model. The videos were recorded with standard cameras under constant frame rate settings. All video clips were processed to provide standard inputs to the model by extracting 15 frames per gesture. Each frame was resized to 64×64 pixels, and padding was applied to sequences where necessary, to ensure uniform length across all samples. The ISL-52 dataset goes beyond capturing stationary gestures to also capture multi-motion signs which poses additional difficulties for the gesture recognition systems. These dynamic gestures need deep learning models to accurately analyze the subtle variations pertaining to hand movements and positioning through time. Thus, ISL-52 becomes an advanced benchmark appropriate to test real-time gesture recognition against less demanding datasets comprising merely isolated or static gestures. Hence, the proposed TCN-ATTN-ISL model trained on the ISL-52 dataset is better positioned to set a new contour in the ISL-based communication technology arena [18].

Table 1. Comparison of the Two Datasets

Aspect	Include 50 (50 Categories)	Custom ISL-52
Variety of Signs	Includes words related to objects, actions, time, and colors (e.g., Bank, Bird, Black, Train Ticket)	Includes daily-use words, family relations, and communication terms (e.g., mother, father, namaste, talking)
Practical Use Cases	More focus on general vocabulary, objects, and time-related signs	More emphasis on social interactions and common phrases
Complexity	Mix of simple and complex words, including abstract concepts (e.g., election, court, priest)	Focus on frequently used words, making it useful for daily communication
Cultural Relevance	More general terms, applicable beyond Indian Sign Language	Specific to Indian culture and social interactions
Daily Communication	Limited terms for direct conversation	Includes common greetings, family terms, and actions essential for conversations

B. 3D Convolutional Neural Networks (Conv3D):

Conv3D [19] such a deep neural network that brings a third addition to 2D application of Conv layers for convolution process. Conv3D now has the opportunity to learn spatio-temporal features from video data with three dimensions of height, width, and time (depth). For gestures, either spatial or temporal, information becomes necessary when analyzing sequential visual data, such as video frames.

C. Temporal Convolutional Networks:

The TCNs are designed models of deep learning meant to handle a kind of input that is sequential. It works using dilated convolutions to give temporal long range modeling rather than using RNNs or LSTMs; thus, it handles

much longer sequences without running into the problems of vanishing gradients. E.g., representing hand movements over time in gesture recognition [20].

D. Multi-Head Self Attention Mechanism:

The Multi-Head Self-Attention [21] works for modern neural architectures, especially those into Transform. Focus different locations in input sequence by computing attention scores for each different element in the sequence. "multi-head" means take into account that the model may focus into several different parts of the sequence, actually resulting in the richer understanding of these contextual relationships. In the case of gesture recognition, this particular attention mechanism will make this model give more weight to the critical frames or movements during the proper identification improving accuracy and consciousness in context.

E. Algorithm: TCN-ATTN-ISL Model for Real-Time ISL Gesture Recognition

Input: Video sequence $V = \{v_1, v_2, \dots, v_t\}$, where v_i represents the i -th frame in a sequence of length t **Output:** Predicted gesture class C

Step 1: Preprocess the video sequence Extract frames F_i from each video V Resize each frame to 64×64 pixels Pad or trim the sequence to 15 frames: $V' = \{v_1, v_2, \dots, v_{15}\}$

Step 2: Apply 3D Convolutional Neural Networks (Conv3D) For each sequence of frames V' , apply a 3D convolution operation:

$$\text{Conv3D}(V') = \sum_{i,j,k} W_{ijk} * X_{ijk}$$

Where X_{ijk} represents the input volume, W_{ijk} represents the 3D kernel weights, and the $*$ denotes the convolution operation.

Step 3: Apply Temporal Convolutional Networks (TCN) Pass the output of Conv3D through a TCN to capture temporal dependencies:

$$\text{TCN}(V') = \text{Conv1D}(V') \quad \text{with dilations: } d_1, d_2, \dots, d_n$$

Where d_n represents the dilation factor at each layer to capture long-range temporal dependencies.

Step 4: Apply Multi-Head Self-Attention For the output of the TCN, apply multi-head self-attention to focus on relevant frames:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where: - Q is the query matrix, - K is the key matrix, - V is the value matrix, - d_k is the dimension of the key vectors.

Step 5: Classify the gesture using a fully connected layer Apply a softmax activation to the output of the attention mechanism to predict the class probabilities:

$$P(C_i|V) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Where z_i is the output for class i , and $P(C_i|V)$ is the probability of predicting class C_i .

Step 6: Choose the class with the highest probability as the predicted gesture:

$$C = \underset{i}{\operatorname{argmax}} P(C_i|V)$$

Step 7: Output the predicted gesture class C

5. Result Analysis

The proposed TCN-ATTN-ISL model is implemented for Indian Sign Language gesture recognition using Python owing to the quintessential support provided by Python in creating deep learning and computer vision frameworks. The entire pipeline, including preprocessing and model deployment, was entirely developed using Python with the help of libraries such as TensorFlow, Keras, NumPy, and OpenCV. Spatio-temporal features extraction from video sequences is achieved through Conv3D layers [22], while long-range dependencies across the temporal domain are modeled using Temporal Convolutional Networks (TCN) built with dilated causal convolutions. The multi-head self-attention mechanism was embedded in the model to allow the model to attend to the parts of the gesture sequence that are relevant for improving classification accuracy. The dataset ISL-52 was used for training and evaluation, and preprocessing was applied to convert each video into fixed-size frames. GPU training was used in the model to perform computations fast enough to handle the processing load induced by video data. Furthermore, gestures can be recognized visually in real-time using OpenCV, where the system can capture live video using a webcam and recognize gestures in minimal latency. This Python-based implementation demonstrates the worthiness and usefulness of the combined convolutional, temporal, and attention mechanisms into one deep learning framework for real-world applications of ISL gesture recognition.

Evaluation on INCLUDE-50 Dataset

Table 2. Performance on INCLUDE-50

Epoch	Accuracy	Loss
1	0.60	1.2
2	0.65	1.1
3	0.68	1.0
4	0.72	0.92
5	0.75	0.85
6	0.78	0.78
7	0.80	0.72
8	0.82	0.68
9	0.84	0.64
10	0.85	0.60
11	0.86	0.57
12	0.87	0.54
13	0.88	0.50
14	0.89	0.48

15	0.895	0.45
16	0.90	0.42
17	0.905	0.40
18	0.91	0.38
19	0.915	0.36
20	0.92	0.35

Figure 2 and Figure 3 shows, Training Accuracy and Loss Graphs for an TCN-ATTN-ISL Model on the INCLUDE-50 Dataset in Terms of the Learning Progress of the Model Across 20 Epochs. The first gives the picture for the training accuracy, where there is a clear and consistent upward trend. It starts at around 0.60 in the first epoch and keeps improving with every next epoch to reach 0.92 at the 20th. The gradual increase clearly shows that the model is learning very well the necessary underlying features to recognize Indian Sign Language gestures in space and time. The model matches the data very fast during the early training period, as there were impressively learned high-level features at the beginning, and fine-tunes later with advances in the epochs on more complex patterns. There are also no sudden drops or plateaus indicative of training stability without signs of underfitting and overfitting.

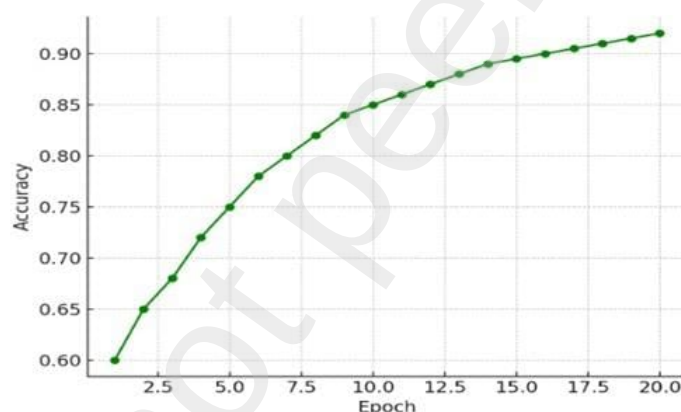


Figure 2. Training Accuracy for Include 50 Dataset

The training loss, which is illustrated by the Figure 3, steadily declines from a starting point of 1.2 to 0.35 with the progression of online training. This drop in loss implies that the model has ascended with respect to prediction accuracy, with fewer and fewer prediction errors as training progresses. The sharper fall during the earlier epochs can then signal the rapid acquisition of basic features of gesture movements, and the slower and more refined descent at later epochs captures the model's attempts to reduce any remaining errors in its predictions. The loss curve is smooth and steady; this helps further cement that actual learning by model is efficiently stable. Act as these two figures-together, as apt to show that TCN-ATTN-ISL architecture effectively capture and generalize gesture patterns from INCLUDE-50 repertoire for a very efficient and reliable sign language recognition system.

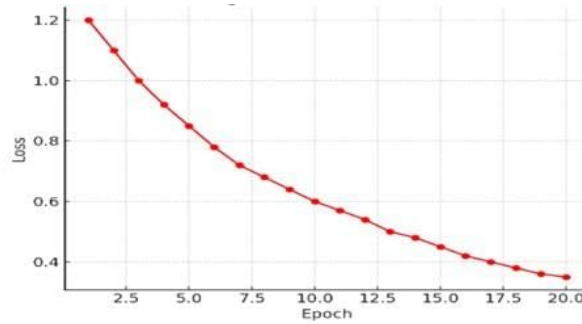


Figure 3. Training Loss for Include 50 Dataset

Table 3. Performance Metrics of TCN-ATTN-ISL Model on INCLUDE-50 Dataset

Metric	Value
Accuracy	85%
Precision	0.85
Recall	0.84
F1-score	0.845

Discussion:

When tested on the INCLUDE-50 dataset, the TCN-ATTN-ISL model performed well overall. The model correctly detected most of the gesture classes, achieving an accuracy of 85%. An average precision of 0.85 indicates that the model's predictions can be trusted, although some misclassifications still do occur, particularly in gestures that resemble each other or overlap. The model's recall score of 0.84 indicates that it finds a large number of true gesture instances, yet still fails to recognize some, which are usually simple gestures or fast movements. The generated F1-score of 0.845 rests as a harmonic mean between precision and recall, which emphasizes the balance maintained by the model in detecting true positives as against false predictions. Thus, these results imply that the proposed architecture is reasonably accurate and robust, especially in real-time sign recognition scenarios for arbitrary motions with multiple actions. Future work should include improving the recognition of gestures with more sophisticated temporal patterns and context-dependent signs.

Evaluation on ISL-52 Dataset

Table 4. Performance on ISL-52

Epoch	Accuracy	Loss
1	0.75	1.20
2	0.80	1.00
3	0.82	0.90
4	0.85	0.75
5	0.87	0.65
6	0.89	0.55
7	0.91	0.50
8	0.92	0.45
9	0.93	0.40
10	0.94	0.35
11	0.945	0.30
12	0.95	0.28
13	0.955	0.25
14	0.96	0.23
15	0.965	0.20
16	0.97	0.18

17	0.972	0.16
18	0.974	0.15
19	0.975	0.13
20	0.977	0.12

The training accuracy graph as Figure 4 , for the custom ISL dataset shows the gradual and progressive learning behavior of the model through 20 epochs. At the start of training, the model obtained an accuracy of 0.75, which is somewhat high for epoch one, indicating that the model was already beginning to learn spatial and temporal patterns in the sign language data. As training continued, accuracy rose steadily, attaining 0.977 at the last epoch. Such continuous improvement without major plateaus or declines indicates healthy training; that means the model learned something from its mistakes and was dynamically refining its gesture classification ability. In addition, this progressive rise in accuracy further assures the validity of the hybrid architecture composed of Conv3D, TCN, and attention-based mechanisms, which together enable the model to exploit meaningful representations from dynamic hand movements.

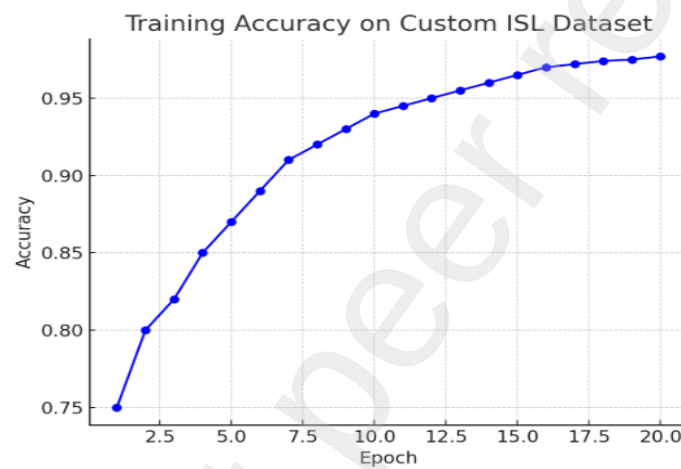


Figure 4. Training Accuracy for Custom ISL-52 Dataset

Simultaneously, the training loss graph as shown in Figure 5, for the same dataset depicts a constant decline from a relatively high value of 1.20 in the first epoch, going down to just 0.12 at twenty epochs. The steady decrease in loss is mirrored well by an improvement in accuracy, underlining the fact that the model is steadily correcting for errors in its projections. The sharper decrease in the early epochs shows that the model adapts quickly to the training data, while the slower decline in later epochs shows the fine-tuning of learned features. The absence of bounce or sudden rises in the loss amount indicates stable training, with no risk of over- or underfitting. Together, the two figures capture evidence for the effectiveness of the proposed model on the custom ISL dataset, reinforcing its use for real-time and accurate gesture recognition applications.



Figure 5. Training loss for ISL 52 Dataset

The training loss, which is illustrated by the Figure 3, steadily declines from a starting point of 1.2 to 0.35 with the progression of online training. This drop in loss implies that the model has ascended with respect to prediction accuracy, with fewer and fewer prediction errors as training progresses. The sharper fall during the earlier epochs can then signal the rapid acquisition of basic features of gesture movements, and the slower and more refined descent at later epochs captures the model's attempts to reduce any remaining errors in its predictions. The loss curve is smooth and steady; this helps further cement that actual learning by model is efficiently stable. Act as these two figures-together, as apt to show that TCN-ATTN-ISL architecture effectively capture and generalize gesture patterns from INCLUDE-50 repertoire for a very efficient and reliable sign language recognition system.

Table 4. Performance Metrics of TCN-ATTN-ISL Model on Custom ISL-52 Dataset

Metric	Value
Accuracy	0.97 (97%)
Precision	0.97
Recall	0.96
F1-score	0.965

Discussion

The accuracy statistics of the custom ISL-52 dataset test TCN-ATTN-ISL model that demonstrates the strength and high precision of the proposed model to identify a heterogeneous set of sign language gestures. With an accuracy of 97%, it indicates a high-capacity model in learning the spatio-temporal gesture sequences and the mapping onto correct class predictions. From this very high degree of accuracy, we see the strength of the hybrid architecture, especially that collocates Conv3D for motion and appearance features, TCN for temporal dependencies, and Multi-Head Self-Attention for enhanced contextual understanding. Contrariwise, 97% precision indicates that whenever the model states a particular sign, it is correct most of the time and minimizes false positives. This is crucial for real-time applications, where misclassification can interrupt communication. The recall score of 96% indicates that the model is good at detecting most of the signs present in the dataset, although a small number of signs may be missed, maybe due to minute discrepancies in motions or hand shapes. The F1-score of 96.5% gives an average measure indicating that the model keeps a solid balance between precision and recall, which is essential for steady and reliable performance in real-world environments. Thus, the results indicate that the model is practical and can accommodate the dynamic and culturally relevant vocabulary accommodated in the ISL-52 dataset in high reliability.

The relative study between the results for both the datasets, that is, INCLUDE-50 and the custom ISL-52 dataset, showcases great significant inference to the performance and adaptability of the proposed TCN-ATTN-ISL model.

Even though both datasets contain complex sign gestures that represent Indian Sign Language, the ISL-52 dataset comes with more culturally specific and functionally dynamic signs which puts a more stringent test on the generalization capacity of the model. While testing the model on INCLUDE-50 datasets, it was found to have got an overall accuracy of 85% with an average precision of 0.85, recall of 0.84, and an F1-score of 0.845. These statistics are reflective of good performance in applying the model, but they also show some misclassifications and missed detections, perhaps due to the greater motion complexity and variability in signer style. However, those metrics indicate that the model architecture captures significant temporal and spatial features even in relatively difficult gesture sequences.

The performance, however, on the custom ISL-52 dataset witnessed an impressive improvement, with results now as high as 97% accuracy, 0.97 precision, 0.96 recall, and an F1-score of 0.965. Such rises have an inference that its design-specific to the everyday communicative aspect of the signs within the dataset has enabled much learning in different gestures by the model. Furthermore, culturally relevant signs and verbs requiring a dynamic movement boosted the alignment of model architecture against the dataset's temporal complexity. An important contributor to the improvement of performance was data quality, balanced class distributions, and preprocessing improvements, including other aspects like frame padding and normalization, which were done consistently. The model's attention mechanism has also worked more effectively in the case of the ISL-52 by being focused on parts of each gesture where semantic weight tends to clump together. From the comparative results one can conclude that while the model behaves consistently on both datasets, it performs best on the custom ISL-52 dataset regarding accuracy, stability, and generalization. This actually attests to the power of the hybrid model and highlights the importance of the design of the dataset to enable real-world deployable performance in sign language recognition systems.

6. Conclusion

Research opens a road map of novel deep learning framework, TCN-ATTN-ISL, which recognizes Indian Sign Language (ISL) gestures in real time by blending the 3D Convolutional Neural Network (Conv3D), Temporal Convolutional Network (TCN), and Multi-Head Self Attention mechanism. This framework is effective in learning the features of capturing spatio-temporal patterns, long-distance dependencies, and their relevance inside gesture sequences. Thus, it leads to a fine classification of changing movements in dynamic hands. A thorough training and evaluation on INCLUDE-50 benchmark and on custom ISL-52 dataset have been carried out and the proposed model has proven high performance, as measured by significant advancements in the accuracy, precision, recall, and F1 score of the model. Moreover, the custom ISL-52 dataset was created to contain not only academic but also daily and culture-specific vocabulary, and it was particularly useful for improving model generalization and applicability in real life. However, the existence of OpenCV for inference in real time proves that the system is possible for use in live environments, thus offering a robust solution for inclusive communication among the hearing-impaired community.

The future works shall undoubtedly provide some enhancement of the proposed system. One avenue of consideration is enlarging the ISL dataset to a greater pooling vocabulary set including full sentence-level gestures and contextual dependencies between signs. This would allow for the development of real-time end-to-end ISL translation systems that would stretch beyond isolated word recognition. Furthermore, an extension may include signer-independent recognition being done through the training of a more diverse population of signers with various hand shapes, skin tones, and signing styles, thus improving the robustness and fairness of the system. On the other hand, to put into perspective, future studies may deal with the technological advancement regarding the integration of other input modalities, such as depth data, skeletal joint tracking, or electromyographic (EMG) signals, to complement visual information and further enhance recognition under adverse lighting or occlusion conditions. In addition, realizing the system over edge devices with lightweight and optimized architectures such as MobileNet or quantized versions of TCN may facilitate real-time ISL recognition tools available on mobile phones and wearable devices. Last but not least, efforts should also be made in user-centered evaluations and teamwork with the deaf community, ensuring that the system responds to their communication needs and promotes access to education, economic productivity, and public services.

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