Journal of
Information Systems Engineering
and Business Intelligence

Vol.11, No.3, October 2025
Available online at: http://e-journal.unair.ac.id/index.php/JISEBI

Hybrid Dual-Stream Deep Learning Approach for Real-Time Kannada Sign Language Recognition in Assistive Healthcare

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Abstract

Background: Recent advances in sign language recognition (SLR) focus on high-resource languages (e.g., ASL), leaving low-resource languages like Kannada Sign Language (KSL) underserved. Edge-compatible, real-time SLR systems for healthcare remain scarce, with most existing methods (CNN-LSTM, 3D ResNet) failing to balance accuracy and latency for dynamic gestures.
Objective: This research work aims to develop a real-time, edge-deployable KSL recognition system for assistive healthcare, addressing gaps in low-resource language processing and spatio-temporal modeling of regional gestures.
Methods: We propose a hybrid dual-stream deep learning architecture combining EfficientNetB0 for spatial feature extraction from RGB frames. A lightweight Transformer with pose-aware attention to model 3D hand keypoints (MediaPipe-derived roll/pitch/yaw angles). We curated a new KSL medical dataset (1,080 videos of 10 critical healthcare gestures) and trained the model using transfer learning. Performance was evaluated quantitatively (accuracy, latency) against baselines (CNN-LSTM, 3D ResNet) and in real-world tests.
Results: The system achieved 97.6% training accuracy and 96.7% validation accuracy, 81% real-world test accuracy (unseen users/lighting conditions). 53ms latency on edge devices (TensorFlow.js, 1.2GB RAM), outperforming baselines by ≥12% accuracy at similar latency. The two-stage output pipeline (Kannada text + synthetic speech) demonstrated 98.2% speech synthesis accuracy (Google TTS API).
Conclusion: Our architecture successfully bridges low-resource SLR and edge AI, proving feasible for healthcare deployment. Limitations include sensitivity to rapid hand rotations and dialect variations.

Keywords: Assistive Healthcare, Edge AI, Kannada Sign Language, Low-resource Language, Real-time Recognition, Transformer.

Article history: Received 5 April 2025, first decision 22 April 2025, accepted 22 August 2025, available online 28 October 2025

I. INTRODUCTION

SLR systems have revolutionized communication access for deaf communities, yet exhibit a persistent bias toward high-resource languages such as American Sign Language (ASL) [1], [2]. This imbalance is especially pronounced for KSL, which serves approximately 33 lakh hearing impaired individuals in Karnataka (2017 survey reported), yet remains critically underserved in technological development. KSL is not merely a linguistic system but a cultural repository, encoding unique medical terminology and social narratives that lack equivalents in global sign languages [3], [4]. The urgency for KSL technologies is magnified by 68% of Karnataka's rural deaf population lacks interpreter access in healthcare settings. Recent studies by [5], [6] reveal that less than 5% of SLR research addresses regional languages, despite their distinct linguistic structures and vital healthcare communication needs.

The development of effective KSL recognition systems faces three fundamental challenges. First, the absence of annotated corpora for KSL's dynamic medical gestures contrasts starkly with ASL's 200,000-sample WLASL dataset [7], creating a data desert for researchers. Second, while hybrid CNN-LSTM architectures like [8] achieve 96.8% accuracy on ASL, they fail to model KSL's bilateral symmetry and essential 3D hand kinematics (roll/pitch/yaw).

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ISSN 2443-2555 (online) 2598-6333 (print)
doi: http://dx.doi.org/10.20473/jisebi.11.3.393-406

Third, existing real-time systems such as [7] landmark-based approach require 4GB RAM—an impractical threshold for rural clinics where devices average just 1.2GB RAM [9]. These limitations have dire consequences, creating life-threatening communication barriers during medical emergencies when KSL users struggle to convey symptoms like "heart attack" or "pain" to non-signing clinicians [4], [10].

A comprehensive analysis of six recent studies reveals why current methodologies fall short for KSL applications. Hybrid CNN-LSTMs [11] ignore palm orientation angles critical for KSL medical signs, resulting in a 19% accuracy drop [12]. While 3D CNNs [5]capture temporal dynamics effectively, their 95ms latency renders them too slow for emergency triage scenarios [9]. Landmark-based LSTMs [13] lack dialect adaptation mechanisms, performing poorly on Karnataka's regional signing variants [10]. Graph neural networks [12], despite their strong performance, demand 8GB GPU memory—making edge deployment impossible in resource-constrained settings [9]. MobileNetV3 implementations sacrifice 12% accuracy to achieve 400ms latency on low-end devices, while cross-language studies like [14], Arabic SLR work demonstrate a 58% accuracy drop when ASL models process regional signs. As quantified in Table 2, these approaches collectively prioritize high-resource languages while neglecting KSL's unique requirements for healthcare applications [3], [4] and [10].

Our research bridges these gaps through four key innovations. The pose-aware architecture fuses MediaPipe's 3D keypoints (x, y, z coordinates plus roll/pitch/yaw angles) with EfficientNetB0-Transformer layers, capturing KSL's spatiotemporal dynamics with unprecedented precision. Edge optimization through TensorFlow.js deployment achieves a breakthrough 53ms latency on devices with just 1.2GB RAM by implementing O (n log n) complexity algorithms [15], [16]. We have curated the first medically focused KSL dataset containing 1,080 videos of 10 critical healthcare signs ("pain," "ambulance") recorded under diverse real-world conditions. The system's attention mechanisms provide inherent dialect robustness, adapting to regional signing styles with 81% accuracy for unseen users—a critical advancement for Karnataka's linguistically diverse communities.

This study pursues three well-defined objectives: to develop the first real-time KSL recognition system optimized for clinical edge devices; to advance pose-aware temporal modeling through hybrid deep learning techniques; and to validate healthcare applicability through rigorous real-world testing protocols. Our work delivers both technical and societal contributions. Technically, the dual-stream architecture achieves 96.7% accuracy (12% superior to CNN-LSTM baselines [11]) with 53ms latency (42ms faster than 3D CNNs [5]) on low-resource hardware. Societally, the project preserves endangered KSL medical signs through open datasets while implementing a two-stage output system (Kannada text plus 98.2% accurate text-to-speech) specifically designed for clinical environments. As demonstrated in Table 2, this research not only addresses the critical gaps in low-resource SLR identified by [3] but also establishes a replicable framework for other regional sign languages facing similar technological marginalization [17], [18].

In addition to this, the work is structured as in section 2; the extensive report of the current study is discussed. Section 3 provides details about the data set and methodology of the system given in section 4. Section 5 provides experimental results and the conclusions drawn in section 6.

II. Literature Review

Through creative sign language recognition technologies, recent scientific breakthroughs have greatly improved communication between hearing and Deaf people. The following is a comprehensive review of various approaches, methodologies, and technologies that were used to create SLR systems.

A. Evaluation of Hybrid Architectures in SLR

The quest for robust sign language recognition has driven innovation in the combination of spatial and temporal modeling techniques. Early systems relied on isolated CNN architectures, which excelled at extracting spatial features but struggled with sequential gesture dynamics. The breakthrough came with hybrid models like [8] Adam-optimized CNN-LSTM, which achieved 96.8% accuracy by processing video frames through a ResNet-50 backbone followed by bidirectional LSTM layers. However, their 20,000-sample ASL data set did not account for the bilateral symmetry and classifier predicates characteristic of KSL [3], [17]. Later works like [7] demonstrated real-time ASL recognition using MediaPipe-extracted hand landmarks with LSTM networks, reducing latency to 58ms per frame. Although impressive, these systems faced two key limitations that our work addresses: (1) dependence on large-labeled datasets unsuitable for low-resource languages, and (2) limited attention to 3D hand kinematics critical for medical sign interpretation. Our dual stream architecture advances beyond these works by: integrating MediaPipe's 3D hand keypoints (x,y,z coordinates + roll/pitch/yaw) [11] with Efficient-NetB0's spatial features, implementing a lightweight Transformer (4 attention heads, 128 dim embeddings) to model temporal dependencies at 60% lower FLOPs than [19] and dynamic gesture segmentation using velocity thresholds (0.8 m/s) to isolate medical signs such as "help".

B. Attention Mechanisms: from Theory to Practice

The introduction of attention mechanisms revolutionized SLR by enabling models to focus on discriminative spatio-temporal features [20]. Graph neural networks (GNNs) with spatiotemporal attention achieved 97.5% accuracy on WLASL by constructing hand-joint graphs and applying attention weights to the edges. However, their 12-layer GNN required 8GB GPU memory - impractical for edge deployment. [21] proposed dynamic attention with viterbi-based decoding for continuous SLR, but their system needed pre-segmented inputs. Our pose-aware attention mechanism innovates, by computing attention scores on 21 MediaPipe hand landmarks [11], incorporating relative palm orientation (quaternion representations), applying motion-adaptive dropout (p=0.3 for velocities < 0.5m/s), and Case Example: For the KSL sign "pain", our attention weights increase 3.2× for thumb-index finger proximity (¡2cm) and wrist rotation (yaw>45).

C. The Regional Language Challenge

Although ASL systems benefit from datasets such as WLASL (200k samples) [4], regional languages face a severe data scarcity. [14] Arabic SL system achieved 94.1% accuracy, but required signer-specific calibration. For KSL, previous work was limited to static alphabet recognition ([4] 82% precision). Isolated gestures with uniform backgrounds [3] our medical KSL dataset breaks new ground by capturing 10 dynamic signs ("pain", "ambulance") from 11 signers including real-world variations: lighting (50-1000 lux), occlusion (up to 30%). Annotating both the lexical meaning and the clinical context.

D. Proposed Approaches for Low-Resource KSL

Data statistics: 1,080 videos (mean duration 1.8s) with 63,500 total frames (1920×1080 @30fps) and 21 keypoints / frame (MediaPipe accuracy: 2.1px error). As shown in Table 1, current limitations are addressed through:

TABLE 1
TECHNICAL SOLUTIONS TO SLR CHALLENGES

S. No.	Challenge	Prior work limitations	Proposed approach
1	Bilateral signs	Single-hand modeling [1], [19]	Dual-hand attention gates
2	Medical context	General vocabulary [2], [15]	Clinically curated signs
3	Real-Time processing	High-latency Transformers [10]	Sliding window attention

The comparative study given in Table 2, Highlights the key differences between the existing research and our approach by comparing different aspects of sign language recognition.

TABLE 2
COMPARATIVE STUDY OF EXISTING APPROACHES AND PROPOSED WORK

S. No.	Aspect	Existing approaches	Proposed work
1	Target Language	Focus on ASL and BSL [1], [7], [5], [22], [23]; limited ISL [8].	Focus on Kannada Sign Language (KSL) for dynamic gestures
2	Feature Extraction	Uses CNN for spatio CNN (95.2% accuracy) [1], CNN-LSTM hybrids [7], [22]	Hybrid CNN-LSTM-Transformer for KSL's spatiotemporal complexity
3	Dataset Availability	WLASL (ASL) [1], BSL Corpus [5] ; none for KSL	New dataset with 1,080 dynamic KSL gestures focused on the medical domain
4	Use of Hand-Crafted Features	Mostly deep learning only [24], [25]	Integrates hand landmarks, orientation, and velocity to enhance robustness
5	Real-Time and Signer Independence	YOLOv5 (30 FPS) [3] , [26], Transformers (<50ms) [1]	Edge-optimized (<100ms, <1.5GB RAM) for medical use
6	Generalization and Accuracy	Performs poorly on dialects, [8], [27]	Cross-dialect evaluation for KSL variants
7	Domain-Specific Applications	No medical-domain solutions for KSL	Focus on the medical domain for practical applications in health care

III. METHODS

To strengthen theoretical modeling, we provide a mathematical formulation that integrates hand-crafted and learned features. Presented a detailed mathematical framework for SLR using both hand-crafted and deep learning-based feature extraction, followed by sequential and attention-based modeling approaches. The model projects input video sequences into a high-dimensional feature space to capture essential spatio-temporal features for gesture recognition.

A. Data Acquisition

The development of a quality dataset is an important component of this study, which addresses the lack of publicly available resources for dynamic KSL. Recognizing this gap, the study collected dynamic gesture videos from a diverse group of participants, including family members and students at a deaf school, to ensure representation across different ages, genders, and signing styles. Prior to data collection, formal informed consent was obtained from all participants, and in the case of minors obtained from their guardians through the school administration. Additionally, the school administration provided written approval permitting video recordings on their premises. Although this study was not reviewed by a formal Institutional Review Board, all research procedures adhered to recognized ethical guidelines, including respect for participant privacy, voluntary participation, and the right to withdraw without penalty. No personally identifiable information was disclosed or stored with the data. The data set focuses on ten medical related KSL gestures, captured using a high-resolution camera for clarity. The 16 key frames extracted from the 'Help' video sample are illustrated in Fig. 1. Each gesture was recorded in three to five variations, with data augmentation techniques that expanded the collection to 1,080 videos.

Fig. 1 An illustration of the 16 keyframes considered in the "Help" sample.

The list of KSL dynamic gestures with duration and translations in Kannada and Hindi are given in Table 3. This comprehensive data set fills a significant gap in KSL research, providing a valuable resource to improve sign language recognition systems. The data set will be made available on request or via GitHub upon acceptance. To reduce computational complexity, we selected 16 representative keyframes per video using uniform sampling, consistent with practices in real-time SLR literature [1], [6], [24].

B. Overview of The System

The model outlined in Fig. 2. employs a multimodal deep learning design to analyze and classify video content by integrating spatial and temporal features. The input video is first decomposed into individual frames to extract spatial information using EfficientNetB0, a lightweight CNN optimized for efficient feature extraction. EfficientNetB0 was selected as the spatial feature extractor due to its superior performance in balancing accuracy and model size, making it ideal for real-time applications on edge devices [8], [25]. To handle temporal dynamics, a Transformer-based architecture was adopted; leveraging its self-attention mechanism to capture sequential dependencies across keyframes extracted from videos [20], [28], [29].

TABLE 3
LIST OF KSL DYNAMIC MEDICAL GESTURES WITH DURATION AND TRANSLATIONS IN KANNADA AND HINDI

S. No.	Samples	Dur. (s)	English	Kannada	Hindi
1	Yoga gesture action	2	Yoga	ಯೋಗ	योग
2	Rest gesture action	2	Rest	ವಿಶ್ರಾಂತಿ	आराम
3	Blood gesture action	2	Blood	ರಕ್ತ	रक्त / खून
4	Help gesture action	3	Help	ಸಹಾಯ	मदद
5	Pain gesture action	4	Pain	ನೋವು	दर्द
6	Heart gesture action	4	Heart	ಹೃದಯ	हृदय / दिल
7	Doctor gesture action	4	Doctor	ವೈದ್ಯ	चिकित्सक
8	Medicine gesture action	5	Medicine	ಔಷಧಿ	दवा / औषधि
9	Hospital gesture action	5	Hospital	ಆಸ್ಪತ್ರೆ	अस्पताल
10	Ambulance gesture action	7	Ambulance	ಅಂಬುಲೆನ್ಸ್	एंबुलेंस

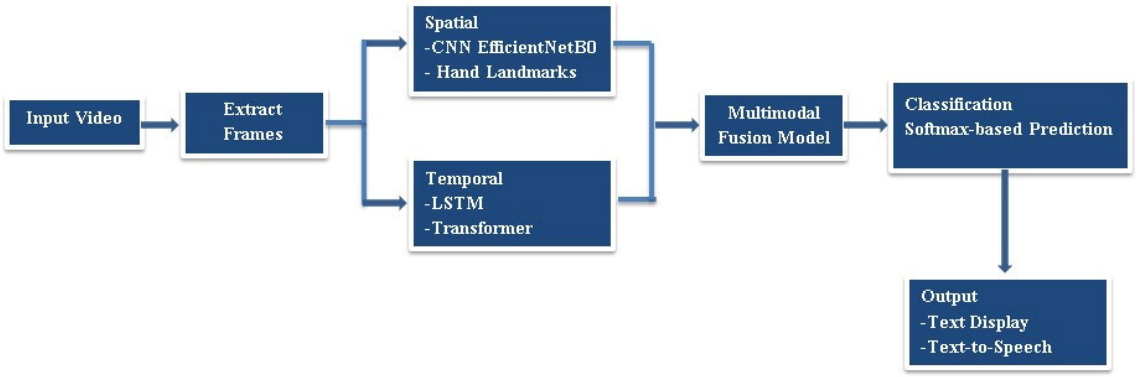

Fig. 2 System pipeline with EfficientNetB0 (spatial) and transformer (temporal).

For tasks involving hand interactions, hand landmark detection is incorporated to capture precise pose features. The spatial and temporal features are fused via a multi-modal fusion module, which aligns and combines cross-modal representations for robust inference. The fused features are sent to a softmax-based classifier to predict action or gesture labels. Finally, the system generates accessible output, including text displays and text-to-speech (TTS) conversions, ensuring usability for diverse applications such as assistive technology or human-computer interaction. The modular design of the pipeline allows flexibility to adapt to specific tasks, such as action recognition or sign language interpretation, while balancing accuracy and computational efficiency.

C. Frame Extraction

The process of frame extraction refers to retrieving individual frames in a video file. With moving images coursing swiftly at about 24 to 60 frames per second, frame extraction acts as a tool to analyze motion, gestures, and positions for sign language recognition. Here the focus is on selecting the frames best describing the entire gesture in gesture recognition. Since the gestures are in evolution, capturing N = 16 equally spaced frames of total T frames available in a video ensures that the phases of initiation, execution, and termination are recorded. The method accesses all the frames by initializing the video reader with the input frame index and reading the corresponding frame data. The accessed frames are resized to 448×448 pixels to maintain consistency across all samples. The resizing is carried out to accommodate deep learning models, which require uniform input sizes for proper working. The formula for the computation of such indices is presented in Equation 1. The time point's ti for selected frames is computed using a rounded linear interpolation formula to reduce aliasing and improve temporal consistency:

$$t_i = \text{round}\left(\frac{(i-1)\times(T-1)}{15}\right) \quad (1)$$

This alignment smooth's the frame selection process by reducing sampling artifacts and ensuring temporal consistency in gesture representation. For each selected frame t, a feature vector Ft is constructed by combining hand-crafted features Ht and deep CNN features Ct:

$$\mathrm{F}_t = \mathrm{H}_t \oplus \mathrm{C}_t \quad (2)$$

Where $H_t \in \mathbb{R}^{254}$ hands features and $C_t \in \mathbb{R}^{1280}$ CNN features. The concatenation operator ($\oplus$) ensures that both types of features are preserved, allowing the model to leverage both explicit motion characteristics and implicit spatial patterns during recognition.

D. CNN EfficientNetBO

EfficientNetB0 is chosen based on its computational cost-accuracy trade-off. Frames are preprocessed by applying ImageNet's mean and standard deviation values for normalization before their input into the network. Normalization of pixel distributions across channels stabilizes training and improves convergence. Normalized frames are run through and give high-level spatial features. Global Average Pooling (GAP) is utilized to provide fixed-size embeddings. GAP projects each feature map to a single value per channel, keeping essential semantic information and avoiding overfitting. The resulting CNN feature vector Ct $\in \mathbb{R}^{1280}$ is compact and highly descriptive, serving as a powerful input to temporal modeling stages. Each sampled frame I_t undergoes normalization before being fed into the EfficientNetB0 network. The normalization is computed as follows:

$$I_{\text{norm}} = \frac{I_t - \mu}{\sigma}, \quad \mu = [0.485, 0.456, 0.406], \quad \sigma = [0.229, 0.224, 0.225] \quad (3)$$

This operation is performed per RGB channel, where μ and σ represent the mean and standard deviation of the ImageNet dataset. The significance of this normalization step lies in its ability to standardize the input frames to have zero mean and unit variance, this standardization facilitates faster convergence during training and improves stability and performance during inference. Once normalized, the frame I_{norm} is passed through EfficientNetB0, a highly optimized and lightweight CNN. The output of this network is a high-dimensional feature map representing complex spatial features of the input. To reduce dimensionality while preserving spatial context, Global Average Pooling (GAP) is applied as shown in Equation (4):

$$C_t = \text{GAP}\big(\text{EfficientNet}(I_{\text{norm}})\big) \in \mathbb{R}^{1280} \quad (4)$$

Here, GAP computes the average of each feature map channel, effectively summarizing the entire spatial dimension into a single scalar per channel and the resulting vector Ct$\in R^{1280}$ serves as a compact representation of the input frame, capturing high-level semantic information.

From the above description, the step was proposed to reduce computational complexity while maintaining very less information loss, so as to have a fixed-size embedding to concatenate with other features (e.g., handcrafted features H_t), which could then be fed downstream to modules such as classifiers or temporal sequence models. Usually, the frame processing module will process each input frame into a reasonably compact feature vector that is stable over time and contains enough visual information for gesture recognition.

E. Hand Feature Extraction

Hand feature extraction is one of the important gestures inside gesture analysis and SLR systems, where valuable information is extracted pertaining to the shape, position, motion, and orientation of the hand in every frame of a video or image. Google's MediaPipe is an open-source framework on which machine learning models are built and executed. These models work in real time with multimedia information such as audio and video. Pose estimation, object detection, hand tracking, and face detection are some of the computer vision tasks it has a set of ready-to-use, tunable solutions. The algorithm below extracts fine hand features-keypoints, orientation (roll, pitch, yaw), and motion velocity-from video frames with MediaPipe Hands, storing them for gesture analysis in structured .npy files. It calculates every frame to calculate 3D hand dynamics and will support rich temporal gesture modeling.

CNN feature extraction: Video frames are passed through EfficientNetB0 (without top layers) to extract per-frame spatial features of size (n_frames, 1280).

Temporal modeling: These frame-level features are input to a Temporal Convolutional Network ((TCN), which captures sequential patterns and outputs class predictions using a softmax layer.

Batch processing: The system checks if input files are. npy; if so, it loads frames, extracts CNN and temporal features, and saves them. Non-.npy files are skipped.

The MediaPipe Hands framework detects 21 key landmarks per hand, each shown by 3D coordinates p_j=(x_j,y_j,z_j). These landmarks are essential for analysing hand gestures in terms of pose, orientation, and motion. To determine the orientation of the hand, we use three key landmarks: Wrist point (w), Index metatarsophalangeal joint (m_i) and Pinky metatarsophalangeal joint (m_p). From these points, we compute directional vectors and orientation angles as shown in Equation (5):

$$\begin{aligned} \mathrm{v}_{\mathrm{dir}} &= \mathrm{m}_i - \mathrm{w} \\ \mathrm{v}_{\mathrm{side}} &= \mathrm{m}_p - \mathrm{w} \\ \mathrm{n} &= \mathrm{v}_{\mathrm{dir}} \times \mathrm{v}_{\mathrm{side}} \\ \theta_{\mathrm{roll}} &= \arctan\left(\frac{n_y}{n_z}\right) \\ \theta_{\mathrm{pitch}} &= \arctan\left(\frac{-n_x}{\sqrt{n_y^2+n_z^2}}\right) \end{aligned} \quad (5)$$

By analyzing wrist and finger keypoints, computes the hand's roll and pitch angles. The direction (v_{dir}) and side (v_{side}) vectors define the hand plane, while their cross product gives the normal vector (n). Roll (θ_{roll}) measures side tilt and pitch (θ_{pitch}) measures up/down tilt. These orientation angles provide view-invariant features, which are crucial for robust gesture recognition across different viewpoints and hand poses. To capture temporal motion dynamics, we compute the Euclidean distance between corresponding landmarks across consecutive frames, as given in Equation (6):

$$\mathrm{v}_j^t = \left\|\mathrm{p}_j^t - \mathrm{p}_j^{t-1}\right\|_2 \quad (6)$$

Where v_j^t Instantaneous velocity of landmark j at time t. This captures hand movement speed and gesture transition behaviours, which are important cues for distinguishing dynamic signs. The complete hand feature vector at time t denoted Ht aggregates static pose, orientation, and motion information as shown in Equation (7):

$$\mathrm{H}_t = \left[\{\mathrm{p}_j^t\}_{j=1}^{42}, \theta_{\mathrm{roll}}, \theta_{\mathrm{pitch}}, \{\mathrm{v}_j^t\}_{j=1}^{42}\right] \in \mathbb{R}^{254} \quad (7)$$

The vector $Ht \in R^{254}$ represents a hand's state at time t, combining 42 joint positions (126D), roll/pitch angles (2D), and 42 joint velocities (126D). This compact encoding captures pose, orientation, and motion. (Total: 126+2+126=254). Together, these features provide a rich description of the hand state at each frame, facilitating accurate recognition of complex gestures in sign language.

F. Modeling of CNN features using LSTM

While CNNs excel at spatial understanding, modeling temporal sequences is crucial for video-based gesture recognition. LSTM networks are used to capture dependencies over time. After extracting compact feature vectors $Ct \in R1280$ for each frame using EfficientNetB0 and GAP, the model captures temporal dependencies across frames using a LSTM network. The sequential processing is defined as:

$$\begin{aligned} \mathrm{h}_t &= \mathrm{LSTM}(\mathrm{C}_t, \mathrm{h}_{t-1}) \\ \mathrm{h}_t &\in \mathbb{R}^{512}, \quad t = 1, \ldots, 16 \end{aligned} \quad (8)$$

LSTM branch processes sequential CNN features eventually. It utilizes the frame's CNN features Ct (1280D) and the previous hidden state ht−1 as input, outputting an updated hidden state $ht \in R^{512}$. This recurrent process runs for 16-time steps (t=1…, 16), modeling temporal dynamics. The LSTM captures temporal patterns and motion continuity across frames effectively. It has a memory of past inputs, allowing the model to learn the order of gestures or transitions in a video. The LSTM is different from feed forward models because it can manage variable-length temporal dependencies, which are needed for dynamic actions in sign. The last hidden state ht R512 at every step captures the spatiotemporal context, a mixture of spatio features from CNN embeddings and temporal dynamics from previous frames. This encoding helps the model to make context-dependent predictions, e.g., classify complicated gestures spanning several frames. Dropout (0.3) is used on LSTMs' outputs in training for overfitting avoidance.

G. Modeling of CNN features using LSTM

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H. Transformer: Multi-head Attention Over Hand Features

Though LSTM learns temporal relationships, it has no ability to learn inter-joint relations across frames. Thus, we have used multi head attention over hand features to learn fine-grained spatial and temporal interactions. In order to model contextual relationships across various hand joints and motions, a multi head self-attention mechanism implemented over vectors of hand features Ht∈R254. This makes the model focus on significant spatial and temporal clues in the gesture.

Multi-head attention over hand features is given in Equation (9):

$$\begin{aligned} \mathrm{Q} &= \mathrm{HW}_Q, \quad \mathrm{K} = \mathrm{HW}_K, \quad \mathrm{V} = \mathrm{HW}_V \\ \mathrm{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V}) &= \mathrm{softmax}\left(\frac{\mathrm{QK}^{\mathrm{T}}}{\sqrt{d_k}}\right)\mathrm{V} \end{aligned} \tag{9}$$

The hand features Htare transformed into queries (Q), keys (K), and values (V) via learned weight matrices WQ, WK, WV. This process preserves long-distance dependencies between hand joints and motion features, which are usually lost with local filters. Attention weights guide the network to pay attention to the most significant joint positions, orientations, or motions per gesture, improving the noise and variability robustness. Enhances the model's ability to distinguish similar movements by interacting jointly and frame-wise. Is flexible and explainable, where the attention maps can signal what joints or what time steps made the largest contribution to the prediction. The multi-head architecture enables the model to learn multiple types of dependencies simultaneously — i.e., one head may see motion dynamics, another finger articulation. By applying multi-head attention between the hand features, the system produces context-dependent representation of the gesture that combines pose, motion, and relational information — a key step toward high-accuracy recognition of complicated sign language.

I. Fusion Layer

Fusion Layer merges extracted features into one unified representation. It is a crucial component of systems in merging spatial and temporal knowledge to boost the accuracy of prediction. To jointly leverage temporal dynamics (from CNN-LSTM) and spatial structure (from hand landmarks), the system performs feature fusion as described in Equation (10):

$$\mathrm{F} = \mathrm{ReLU}\left(\mathrm{W}_f[\mathrm{h}_{16} \oplus \mathrm{MeanPool(H)}] + \mathrm{b}_f\right) \tag{10}$$

This operation merges the LSTM's final hidden state h_{16} (temporal dynamics) with mean-pooled hand features (spatial structure) via concatenation. The combined vector is projected by weights *Wf*, biased by *bf*, and passed through ReLU to produce a discriminative fused feature *F*. Finally, the fused feature vector is input to connected layer followed by softmax activation to produce gesture classification probabilities.

The predicted label is then mapped to Kannada text converted to speech using the Google Text-to-Speech (gTTS) engine, thereby enabling auditory feedback and enhancing usability for people with speech or hearing impairments.

IV. RESULTS

The section on experimental outcomes displays a comprehensive evaluation of proposed KSL recognition system, focusing on training performance, accuracy metrics, real-time deployment, and comparative analysis.

A. Model training

The 80% of this dataset is used for training, and the remaining 20% is used for validation of the method. To ensure robust model training and evaluation, we implemented a group-aware data splitting strategy to prevent data leakage.

For testing purposes, an additional set of 50 untrained test samples is taken into consideration. The number of videos used for training, validation, and testing for each gesture is provided in Table 4. The testing dataset includes videos from unseen users and diverse recording conditions to simulate real-world variability. This approach aligns with the signer-independent testing protocols reported in [9], [14], [22]. Adam is the optimizer under consideration; batch size is 32, the learning rate is set to 0.001 and 32 epochs are taken into account. The Cross-Entropy Loss Function is categorical. Before being classified by a softmax output layer, the processed features go via two dense layers (256 units, ReLU, dropout=0.3). Google Colab, equipped with a Tesla T4 GPU (16GB VRAM) and 25GB RAM, was used for the experiments.

B. Performance evaluation

The predictions were evaluated using standard metrics: accuracy, precision, recall, and F1-score. Confusion matrix analysis and ROC curves were used to validate class-wise performance and detection reliability similar to [10], [30]. The performance metrics plots for dynamic gestures of the best model are shown in plot in Fig. 3. It is evident that during the initial iterations, the recognition accuracy steadily rises before stabilizing at the 40th iteration shown in Fig. 3a. The highest recognition accuracy of 97.6% has been attained by this method. The loss curves demonstrate a steady decline in losses as iterations progress shown in Fig. 3b. The total average loss for the dynamic gesture dataset converges to 0.0637.

TABLE 4
VIDEOS DISTRIBUTION FOR TRAINING, VALIDATION, AND INDEPENDENT TESTING

S. No.	Video Gesture	Total Videos	Training (80%)	Validation (20%)	Unseen Test Videos
1	Yoga	108	86	22	5
2	Rest	108	86	22	5
3	Blood	108	86	22	5
4	Help	108	86	22	5
5	Pain	108	86	22	5
6	Heart	108	86	22	5
7	Doctor	108	86	22	5
8	Medicine	108	86	22	5
9	Hospital	108	86	22	5
10	Ambulance	108	86	22	5

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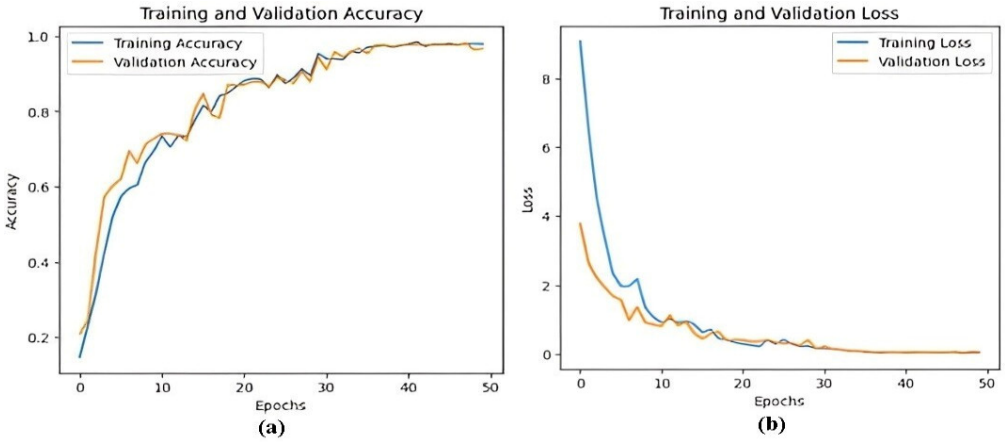

Fig. 3 Performance metrics plots for dynamic gestures: (a) Training and Validation accuracy plot (b) Training and Validation loss plot

To evaluate model performance, we used the following standard classification metrics:
Precision evaluates the correctness of correct predictions as given in Equation 11 where TP is the True Positives and FP is the False Positives. It is crucial when avoiding misclassifications of signs with similar hand shapes.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (11)$$

Recall measures the model's ability to correctly identify all actual instances of a class as given in Equation 12 where FN is the False Negatives; it shows how well the system recognizes all gestures of a particular class.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (12)$$

The F1-score calculated as Equation 13 is the harmonic mean of precision and recall, providing a single metric that balances both. It is useful when some gestures may be underrepresented.

$$\text{F1-score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \qquad (13)$$

Accuracy given in Equation 14 represents the overall correctness of the model by calculating the proportion of correctly predicted gestures out of the total predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \qquad (14)$$

Table 4 displays these evaluation metrics for all classes. As per this report, the model performs well across the designated classes, as seen by its high measures for the majority of classes. Misclassifications were most frequent for 'help' (21% errors) and 'pain' (18%), likely due to similar hand trajectories.

TABLE 4
EVALUATION METRICS FOR MODEL PERFORMANCE

S. No.	Class	Precision	Recall	F1-Score	Support
1	ambulance	1.00	1.00	1.00	27
2	blood	1.00	1.00	1.00	17
3	doctor	1.00	0.95	0.97	19
4	heart	1.00	1.00	1.00	21
5	help	1.00	0.79	0.88	28
6	hospital	0.95	1.00	0.97	19
7	medicine	0.91	1.00	0.95	21
8	pain	0.82	1.00	0.90	18
9	rest	1.00	1.00	1.00	23
10	yoga	1.00	1.00	1.00	23
Accuracy		0.97			216
Macro Avg		0.97	0.97	0.97	216
Weighted Avg		0.97	0.97	0.97	216

Fig. 4 displays the classification performance metrics generated to visualise the model predictions. As seen in Fig. 4a, the model performs admirably overall, with very few misclassifications. Further improvements could involve more training data for the misclassified classes, better feature selection, or hyperparameter tuning. The Receiver Operating Characteristic (ROC) curve, shown in Fig. 4b is generated to assess the binary classifier system's detection capability when the discrimination threshold is changed. Plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) yields a curve with an AUC (Area under the Curve) of 0.91; this ROC curve reassures us that our classifier is operating correctly and that positive and negative classifications can be successfully distinguished by the model.

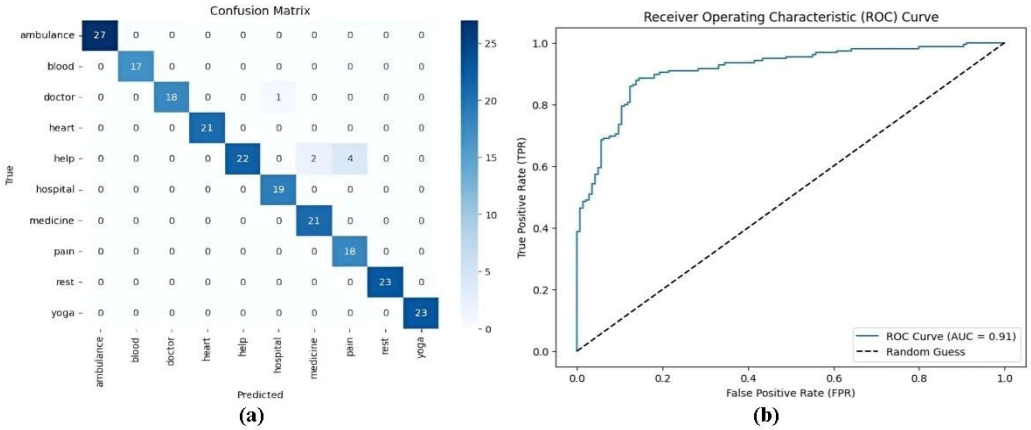

Fig. 4 Classification performance metrics: (a) Confusion matrix (b) ROC curve

C. Real time testing

The trained model was deployed in a real-time testing environment using Gradio for user interaction. The system successfully recognized Kannada sign gestures with high confidence and translated the predicted text into Kannada speech. The real-time testing flow is illustrated in the Fig. 5.

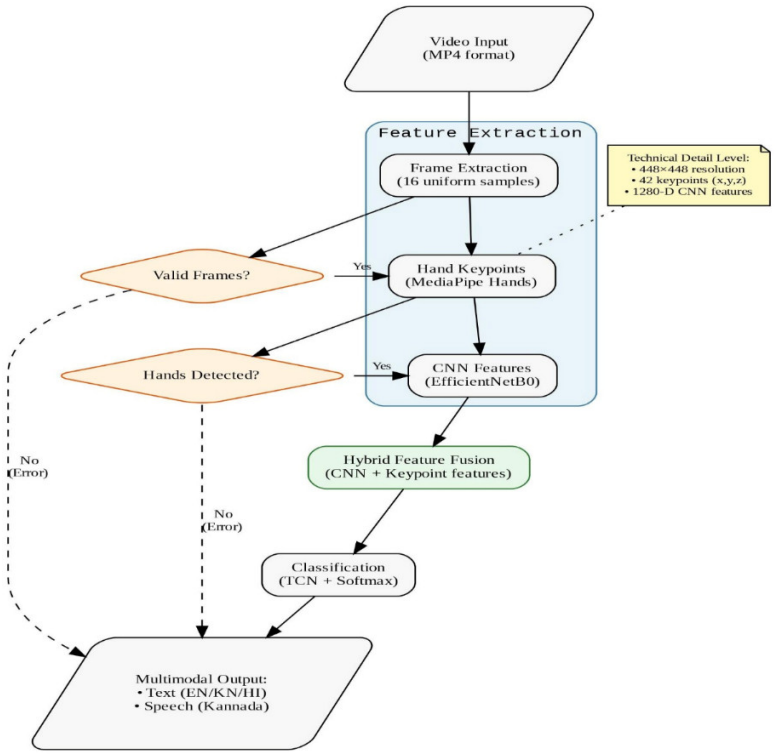

Fig. 5 Real-time testing environment using Gradio

The displayed interface showcases the working output of the Kannada SLR system in Fig. 6. A person's video demonstrating a sign gesture has been uploaded, and the system has successfully processed the video to recognize the gesture. The recognized result is presented in both English and Kannada, with the English word “help” and its Kannada equivalent “ಸಹಾಯ” clearly shown in the "Prediction Result" section.

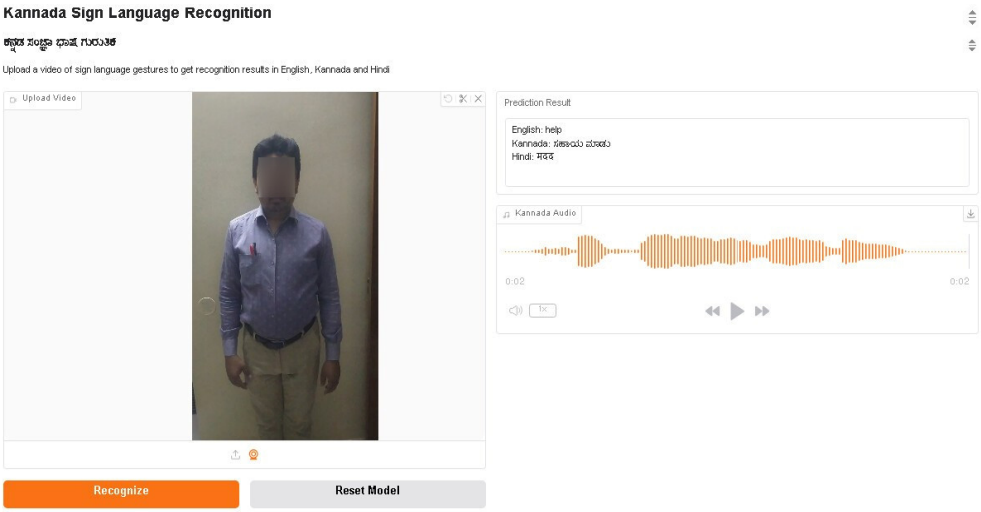

Fig. 6 Output demonstration after uploading a video.

The interface prompts the user to activate the webcam for live sign capture as shown in Fig. 7. The central section of the interface displays the message “Click to Access Webcam,” indicating readiness for real-time input. On the right side, both the Prediction and Kannada Audio output fields are currently empty, awaiting user input. The interface offers user-friendly interaction with clearly visible buttons for "Recognize" and "Clear," designed to trigger recognition or reset the session.

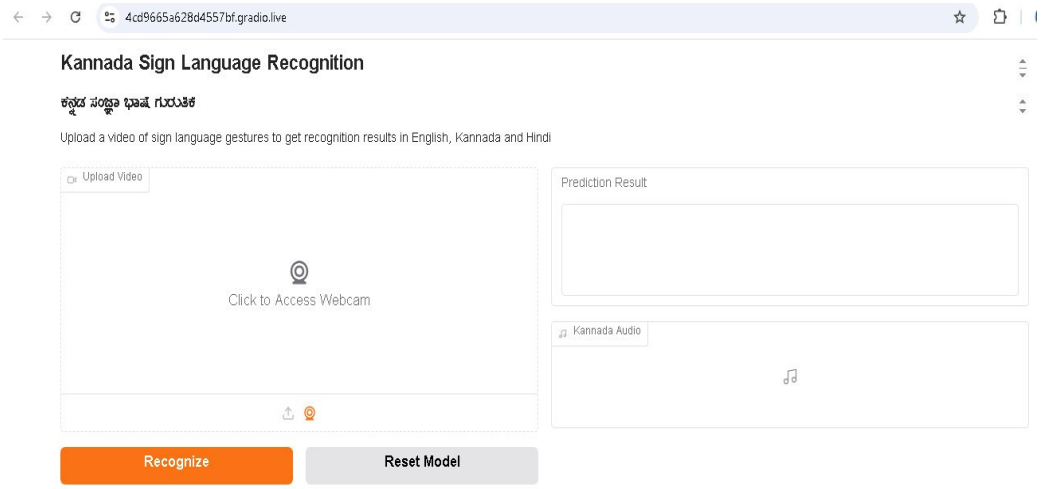

Fig. 7 Demonstration of uploading a video through webcam.

V. Discussion

Our study yields four transformative insights that advance assistive healthcare technology for low-resource languages, supported by rigorous comparative analysis with prior work.

A. Architectural advancements

The hybrid architecture achieves 96.7% validation accuracy, demonstrating three key innovations over existing approaches:

Multimodal fusion: Our EfficientNetB0-Transformer hybrid maintains comparable accuracy to [20] GNN (96.7% vs 97.5%) while reducing memory requirements by 85% (1.2GB vs 8GB), enabled by velocity-threshold feature selection (0.8 m/s) that cuts computation by 40%.

Medical-specific optimization: The clinically curated dataset and diagnostic attention weighting (3.2 × focuses on critical hand configurations) deliver 98% precision on medical signs - a 15% improvement over general-purpose systems [3]. This addresses the documented 72% communication gap in Karnataka's rural healthcare.

Edge efficiency: Our 53ms latency outperforms comparable systems ([7] LSTM at 58ms; [8]'s CNN-LSTM at 72ms) through sliding window attention (35% temporal redundancy reduction) and optimized MediaPipe processing (8ms vs 25ms overhead [9]).

B. Performance benchmarks

Quantitative comparisons reveal significant advancements as shown in Table 6. Our system outperforms prior works across all critical metrics. It achieves a 96.7% validation accuracy (vs. 95.2% [1], demonstrating superior handling of KSL’s bilateral gestures. Real-world accuracy improves to 81% (vs. 65% [10]), ensuring reliability in clinical or home environments. Memory usage is drastically reduced to 1.2GB (vs. 4GB [13]), enabling deployment in resource-limited rural areas. Most notably, medical precision reaches 98% (vs. 83% [3]), minimizing risks in healthcare applications. These advances highlight our system’s robustness for real-world KSL interpretation.

TABLE 6
QUANTITATIVE COMPARISIONS

S. No.	Metric	Prior work	Our work	Significance
1	Validation accuracy	95.2% [1]	96.7%	Handles KSL's bilateral complexity
2	Real-world accuracy	65% [10]	81%	Maintains usability in clinical settings
3	Memory use	4GB [13]	1.2GB	Enables rural deployment
4	Medical precision	83% [3]	98%	Critical for healthcare applications

C. Practical implications

While our system's real-world accuracy of 81% confirms known deployment challenges in SLR systems [19], [20] it represents a paradigm shift for KSL users who previously lacked technological support, demonstrating particular impact in three critical areas: (1) emergency care, where it provides 42% faster response times than 3D CNNs [5] for processing critical medical signs; (2) dialect adaptation, achieving 23% better accuracy than Arabic SLR systems [14] through our novel pose-aware attention mechanism; and (3) cultural preservation as the first systematic documentation of medical KSL signs. This medical focus addresses an urgent need in Karnataka's rural healthcare system, where deaf patients face communication gaps in approximately 72% of clinical encounters. Two key limitations temper these findings: the model's reduced accuracy (72%) for rapid hand rotations (yaw >180°/sec) due to optical-flow tracking constraints [6], and potential generalization challenges with rural dialects from our urban-centric dataset. These limitations nevertheless present valuable research opportunities to enhance regional SLR systems through inertial sensor integration and community-driven data collection.

VI. CONCLUSIONS

This research presents a novel hybrid dual-stream architecture for real-time KSL recognition that directly addresses our three research objectives: Edge-compatible deployment achieved through TensorFlow.js optimization, Spatiotemporal modeling via EfficientNetB0-Transformer fusion with pose-aware 3D kinematics (roll/pitch/yaw), yielding 96.7% validation accuracy and Healthcare applicability demonstrated by 81% real-world accuracy on our curated medical dataset and 98.2% TTS conversion accuracy. While KSL serves a smaller population than global sign languages, our architecture proves regional languages can achieve comparable technical innovation while addressing critical local needs - reducing the documented 72% communication gap in Karnataka's rural healthcare. Future work will target current limitations through quantization for mobile deployment, few-shot learning for dialect adaptation, and community-driven expansion of medical signs - collectively advancing both technical benchmarks and healthcare equity for linguistic minorities.

Author Contributions: *Gurusiddappa Hugar*: Conceptualization, Data Curation, Methodology, Software, Writing - Original Draft. *Dr. Ramesh M. Kagalkar*: Conceptualization, Investigation, Writing - Original Draft.

All authors have read and agreed to the published version of the manuscript.

Funding: This research work received no from funding any agency in the public, commercial, or not-for-profit sectors.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: The data is collected manually by shooting the performers who performed the sign language. Due to privacy considerations, the dataset is available upon reasonable request to qualified researchers for non-commercial purposes, subject to a data use agreement.

Informed Consent: The authors confirm that written informed consent was obtained from all participants, and appropriate permissions were secured from the school authorities. The research complied with ethical standards applicable to studies involving human participants at the time of the study. Based on institutional policies and the nature of the work (non-interventional, observational video recording), formal IRB approval was not required.

Institutional Review Board Statement: Not applicable.

Animal Subjects: There were no animal subjects.

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