Real-Time Sign Language Interpretation Using Deep Learning

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Abstract- *Sign language serves as the primary mode of communication for millions of hearing-impaired individuals worldwide, yet the gap between the deaf community and the hearing world remains a significant barrier. This paper presents a comprehensive, three-subsystem deep learning framework for Real-Time Sign Language Interpretation, encompassing Sign-to-Text conversion, Text-to-Animation synthesis, and Text-to-Image generation. The Sign-to-Text module leverages a Convolutional Neural Network (CNN) trained on MediaPipe-extracted hand landmark vectors, deployed via a Flask backend with OpenCV-based real-time video capture, achieving a classification accuracy of 97.6% across 26 American Sign Language (ASL) gestures. The Text-to-Animation subsystem utilizes Angular 21 and Ionic 8 on the frontend with Node.js/Express and Firebase cloud infrastructure, employing MediaPipe Holistic for body-pose-driven skeletal animation rendering. The Text-to-Image subsystem is a React 19 single-page application powered by a generative deep learning model pipeline, converting descriptive text into contextual sign language visual representations. Extensive experiments demonstrate strong cross-subsystem performance, with MSE of 0.043, RMSE of 0.207, Precision of 96.8%, and Recall of 97.1% on the test set. The proposed integrated framework significantly advances assistive communication technology and establishes a replicable architecture for real-world sign language translation deployment.*

Keywords: Sign Language Recognition, Convolutional Neural Network (CNN), MediaPipe, Deep Learning, Hand Gesture Classification, Text-to-Animation, Computer Vision, Assistive Technology.

I. INTRODUCTION

Sign language is a rich, visual-spatial language used by an estimated 72 million Deaf and hard-of-hearing individuals globally. Despite its widespread usage, a fundamental asymmetry persists: very few hearing individuals possess proficiency in sign language, creating communication barriers that limit educational, professional, and social participation for the deaf community. Human interpreters, while invaluable, are costly, limited in availability, and cannot scale to real-time digital communication contexts. Automated sign language interpretation systems address this gap by providing on-demand, accurate translation between signed and spoken language modalities.

Recent advances in deep learning, computer vision, and mobile computing have created the technical conditions for practical deployment of automated sign language recognition (SLR) systems. Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in spatial pattern recognition, directly applicable to hand gesture and sign classification. MediaPipe, Google's cross-platform framework for perception pipelines, provides real-time, device-local extraction of 21 hand landmarks per hand, enabling robust feature engineering without GPU-intensive full-image classification. The combination of these technologies enables production-grade SLR on consumer hardware.

The scope of effective sign language interpretation, however, extends beyond one-directional gesture-to-text conversion. Deaf users also require systems that translate written or spoken text back into sign language representations, enabling bidirectional communication. This motivates a three-subsystem architecture: (1) Sign-to-Text for real-time gesture recognition; (2) Text-to-Animation for animated sign language avatar rendering; and (3) Text-to-Image for generating contextual visual representations of sign language gestures.

This paper presents an end-to-end deep learning framework integrating all three subsystems into a unified, architecturally coherent system. The Sign-to-Text module is built on Python/Flask with TensorFlow/Keras CNN, OpenCV video pipeline, and MediaPipe landmark extraction, with a Tkinter GUI and pyttsx3 text-to-speech output. The Text-to-Animation module utilizes Angular 21/Ionic 8 frontend with Node.js/Express backend and Firebase cloud services, rendering skeletal animations via MediaPipe Holistic pose estimation. The Text-to-Image module is a lightweight React 19/Vite single-page application with Tailwind CSS. Together,

these subsystems form a comprehensive, deployable solution for real-world sign language interpretation.

The primary contributions of this work are: (1) a high-accuracy CNN-based ASL classifier achieving 97.6% test accuracy; (2) a real-time hand landmark feature engineering pipeline using MediaPipe 21-keypoint vectors; (3) an Angular/Firebase-based Text-to-Animation cloud deployment; (4) a React 19 Text-to-Image generation SPA; and (5) comprehensive comparative evaluation demonstrating state-of-the-art performance across all three subsystems.

II. LITERATURE SURVEY

The field of automated sign language recognition has evolved substantially across multiple research directions. This section surveys the most relevant prior work across five thematic areas.

A. Traditional Computer Vision Approaches

Early sign language recognition systems relied heavily on wearable sensor gloves and marker-based tracking systems. Fels and Hinton pioneered a neural network approach using CyberGlove sensor data for gesture recognition, achieving recognition of isolated signs but requiring intrusive hardware. Starner and Pentland applied Hidden Markov Models (HMMs) to video-based ASL recognition, establishing a foundational non-intrusive pipeline. However, HMM-based approaches are constrained by their Markov assumption of temporal independence and their inability to model complex spatial configurations of the hand. Template matching approaches such as Dynamic Time Warping (DTW) were applied to sign sequence alignment by Lichtenauer et al., but the reliance on hand-crafted features limited generalization to diverse signers and environments.

B. Deep Learning for Gesture Recognition

The emergence of deep learning transformed gesture and sign recognition. Pigou et al. demonstrated that CNNs substantially outperform HMM-based systems on gesture recognition benchmarks, particularly when processing frame-level spatial features. Molchanov et al. extended this to 3D CNNs, incorporating temporal motion information through volumetric convolution over frame sequences. Recurrent architectures, particularly Long Short-Term Memory (LSTM) networks, further improved performance on continuous sign sequences. Cui et al. proposed an iterative training procedure combining CNN feature extraction with LSTM sequence modelling for continuous sign language recognition, achieving competitive performance on the RWTH-PHOENIX weather broadcast corpus. Pu et al. introduced iterative alignment loss for weakly-supervised CTC-based continuous SLR, addressing the sequence-to-sequence alignment challenge without full temporal annotation.

C. MediaPipe-Based Hand Tracking Systems

Zhang et al. introduced MediaPipe Hands, a real-time on-device solution for hand tracking and landmark estimation, achieving 21 3D keypoints per hand at over 30 FPS on mobile hardware. This landmark represents a paradigm shift: instead of classifying raw image pixels, downstream models operate on compact, rotation-normalized landmark vectors, dramatically reducing model complexity and training data requirements. Wentao et al. applied MediaPipe landmarks to sign language recognition using a lightweight MLP classifier, demonstrating that hand keypoints alone provide sufficient discriminative information for isolated sign recognition. CVZone'sHandTrackingModule built on MediaPipe further simplified integration into Python-based real-time pipelines. Subsequent work by Pisharady and Saerbeck showed that landmark-based features generalize better across signers and lighting conditions than pixel-based approaches.

D. Animation and Avatar-Based Sign Synthesis

Sign language synthesis converting text to sign presents distinct challenges from recognition. Early systems relied on pre-recorded video clips stitched by lookup tables, lacking naturalness in transitions. Stroke-based animation approaches using virtual avatars, exemplified by the eSIGN and Vcom3D systems, produced schematic but grammatically accurate sign renderings. More recent work by Stoll et al. applied neural machine translation combined with skeletal pose estimation to generate sign language pose sequences from spoken language text, using the PHOENIX-2014T dataset. Saunders et al. extended this to progressive transformers for sign pose production, achieving state-of-the-art Sign Language Production (SLP) results. The emergence of MediaPipe Holistic for full-body pose extraction enabled real-time skeleton-driven animation without specialized motion capture hardware.

E. Multimodal and Integrated Sign Language Systems

Recent research has moved toward integrated, multimodal systems addressing both recognition and synthesis. Ko et al. proposed a two-stream CNN architecture combining appearance and motion streams for Korean Sign Language recognition, demonstrating the benefit of explicitly modelling temporal dynamics alongside spatial structure. Jiang et al. investigated transformer-based architectures for

sign language translation, applying attention mechanisms to align gloss sequences with spoken language translations. Hardware-integrated systems such as those using Raspberry Pi and Arduino with flex sensors were demonstrated by Sahu et al. for Indian Sign Language, highlighting the potential for affordable deployment. The integration of text-to-speech output via pyttsx3 and Flask web deployment was demonstrated in prototype systems by multiple groups, but comprehensive three-subsystem integration with cloud deployment has not been previously reported. This paper addresses this gap through the proposed unified integrated architecture.

Table 1. Comparative Literature Review of Sign Language Systems

Ref.	Authors	Method	Dataset	Limitation
[1]	Zhang et al., 2020	MediaPipe Hands + MLP	Custom ASL	Isolated signs only
[2]	Pigou et al., 2016	CNN + HMM	ChaLearn	No real-time pipeline
[3]	Molchanov et al., 2016	3D CNN	VIVA Hand	High compute cost
[4]	Cui et al., 2019	CNN-LSTM iterative	PHOENIX-2014	No synthesis module
[5]	Stoll et al., 2020	NMT + Pose Est.	PHOENIX-2014T	No real-time deployment
[6]	Saunders et al., 2021	Progressive Transformer	PHOENIX-2014T	No mobile frontend
[7]	Ko et al., 2019	Two-stream CNN	KSL	Language-specific

The literature review reveals three clear research gaps: (1) existing systems address either recognition or synthesis, not both in a unified framework; (2) no system integrates cloud-based animation rendering with a modern Angular/Firebase architecture; and (3) Text-to-Image generation for sign language visualization has not been combined with real-time recognition and animation synthesis.

III. EXISTING SYSTEM AND ITS DRAWBACKS

A. Existing System Overview

Current approaches to sign language recognition and synthesis fall into three broad categories. Sensor-based systems using data gloves or wrist accelerometers achieve high accuracy for the equipped user but require specialized, expensive hardware incompatible with everyday use. Image-based systems processing raw video frames with CNNs or spatiotemporal models avoid hardware dependency but impose significant computational burdens, limiting real-time performance on consumer devices. Landmark-based systems using tools such as MediaPipe reduce computational cost but existing implementations typically address only one direction of communication — either sign-to-text or text-to-sign — and are rarely deployed in production-grade web or mobile environments.

Text-to-Animation systems are frequently implemented as lookup-table video clip players with limited vocabulary and poor transition quality. These systems do not generalize to novel sentences and fail entirely on out-of-vocabulary signs. Text-to-Image generation for sign language is largely unexplored, with most existing systems showing static reference images without generative capability.

B. Drawbacks of Existing Systems

- Unidirectional communication: Most systems support only sign-to-text or text-to-sign, not both. Bidirectional communication requires independent, disconnected tools with no unified interface.
- Hardware dependency: Sensor-glove systems require specialized equipment unavailable to general users, limiting scalability and accessibility.
- Limited vocabulary: Existing recognition systems typically handle 10–26 static gestures, failing to address the grammatical complexity and continuous nature of real sign language.
- No real-time animation synthesis: Lookup-table animation systems cannot generalize beyond pre-recorded vocabulary and produce unnatural transitions between signs.
- Absence of cloud deployment: Most research prototypes run as local Python scripts with no web or mobile deployment, limiting accessibility.
- No multi-feature integration: Existing systems do not combine CNN spatial classification, LSTM temporal modelling, and MediaPipe landmark extraction in a single cohesive pipeline.
- Poor cross-signer generalization: Systems trained on single-signer datasets exhibit significant accuracy degradation across different signers due to variation in hand size, skin tone, and signing style.
- No Text-to-Image generation: The generation of contextual visual representations of sign language content from text descriptions has not been integrated into existing sign language systems.

IV. PROPOSED SYSTEM

The proposed Real-Time Sign Language Interpretation system is a three-subsystem deep learning

framework providing comprehensive, bidirectional sign language communication support. The architecture is designed for production-grade deployment across web, mobile, and desktop platforms, utilizing modern cloud infrastructure and state-of-the-art deep learning components.

The Sign-to-Text subsystem captures live video via OpenCV, extracts 21-keypoint hand landmarks using MediaPipe, constructs a 63-dimensional feature vector per frame, and classifies the gesture using a trained CNN model (.h5 format loaded via Keras). Classification results are rendered in a Tkinter GUI and converted to speech via pyttsx3. The Flask backend exposes RESTful API endpoints for web integration, enabling browser-based clients to submit frames and receive classified text.

The Text-to-Animation subsystem accepts text input via an Angular 21/Ionic 8 mobile-web frontend, processes the input through a Node.js/Express backend, stores animation metadata in Firestore and Firebase Realtime DB, and retrieves MediaPipe Holistic skeletal animation data from Firebase Storage. Firebase Functions handle server-side processing and Firebase Admin SDK manages authentication and data orchestration. The animation renderer parses skeletal keypoint sequences and drives a 3D avatar in the browser.

The Text-to-Image subsystem is a React 19 single-page application built with Vite and styled with Tailwind CSS. It accepts text descriptions of sign language content and invokes a generative deep learning model pipeline to produce contextual sign language visual representations. Operating entirely client-side without a backend, this subsystem prioritizes simplicity, speed, and accessibility.

The three subsystems are unified under a common design language and share authentication infrastructure, enabling users to seamlessly switch between communication modes within a single session. The system is designed for accessibility compliance and has been validated on AMD Ryzen 3 consumer hardware with cloud GPU offloading for model training.

V. SYSTEM ARCHITECTURE

This section presents the detailed mathematical and architectural formulations underlying the three subsystems of the proposed framework.

A. Convolutional Neural Network Mathematical Formulation

The CNN classifier at the core of the Sign-to-Text module processes two-dimensional feature map representations derived from MediaPipe landmark vectors. The fundamental convolution operation transforms an input feature map x into an output feature map y through a learnable filter kernel w:

$$y(i,j) = \Sigma_m \Sigma_n x(i+m, j+n) \cdot w(m,n) + b$$

where i, j denote the spatial position in the output feature map, m, n index the filter kernel dimensions, w(m,n) is the filter weight at position (m,n), and b is the bias term. This operation extracts spatially local patterns — critical for detecting finger configurations, palm orientation, and inter-finger relationships that characterize distinct signs.

Batch normalization is applied after each convolutional layer to stabilize training and reduce internal covariate shift:

$$\hat{x} = (x - \mu_B) / \sqrt{(\sigma^2_B + \varepsilon)}$$
$$y = \gamma \cdot \hat{x} + \beta$$

where μ_B and σ^2_B are the batch mean and variance, ε is a small constant for numerical stability, and γ, β are learnable scale and shift parameters.

The Rectified Linear Unit (ReLU) activation function is applied element-wise after each convolution, introducing non-linearity essential for learning complex spatial configurations:

$$f(x) = max(0, x)$$

Max-pooling layers with kernel size 2×2 and stride 2 perform spatial subsampling, producing translation-invariant feature representations while reducing computational cost:

$$P(i,j) = max_{(m,n) \in R(i,j)} x(m,n)$$

The final classification layer applies the Softmax activation to produce a probability distribution over K sign classes:

$$\sigma(z)_k = exp(z_k) / \Sigma_j exp(z_j), \quad k = 1, ..., K$$

The network is trained by minimizing the categorical cross-entropy loss:

$$L = -\Sigma_i \Sigma_k y_{ik} \cdot log(\hat{y}_{ik})$$

where y_{ik} is the one-hot ground truth label and $\hat{y}_{ik}$ is the predicted probability for class k on sample i.

B. LSTM Temporal Sequence Modelling

For dynamic gesture sequences requiring temporal context, an LSTM network processes sequential MediaPipe landmark vectors. The LSTM maintains a cell state c_t and hidden state h_t regulated by three gating mechanisms. The forget gate determines what information from the previous cell state to discard:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

The input gate controls what new information is written to the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

The cell state is updated as a combination of the remembered past and newly encoded information:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

The output gate produces the hidden state for the current time step:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(c_t)$$

where σ denotes the sigmoid function, tanh the hyperbolic tangent, ⊙ element-wise multiplication, and W, b are learnable weight matrices and bias vectors. This gated architecture enables selective retention of sign-relevant temporal context over sequences of arbitrary length, directly addressing the vanishing gradient limitation of basic RNNs.

C. MediaPipe Hand Landmark Feature Engineering

MediaPipe Hands produces 21 landmarks per detected hand, each represented as a 3D coordinate (x, y, z) normalized relative to the bounding box of the detected hand. The landmarks follow a standardized anatomical assignment: landmark 0 is the wrist, landmarks 1–4 constitute the thumb (CMC, MCP, IP, TIP), landmarks 5–8 the index finger, 9–12 the middle finger, 13–16 the ring finger, and 17–20 the little finger.

The feature vector for a single hand detection is constructed by flattening the landmark coordinates:

$$v = [x_0, y_0, z_0, x_1, y_1, z_1, \ldots, x_{20}, y_{20}, z_{20}] \in \mathbb{R}^{63}$$

For two-hand signs, the feature vectors for the left and right hands are concatenated to form a 126-dimensional input:

$$v\_combined = [v\_left \mid v\_right] \in \mathbb{R}^{126}$$

Prior to feature vector construction, landmark coordinates are normalized relative to the wrist position to achieve translation invariance:

$$\tilde{x}_i = x_i - x_0, \quad \tilde{y}_i = y_i - y_0, \quad \tilde{z}_i = z_i - z_0$$

This normalization ensures that the classifier is invariant to the absolute position of the hand within the video frame, significantly improving generalization across different signing positions and camera placements.

D. End-to-End Pipeline Architecture

The complete Sign-to-Text processing pipeline follows a sequential transformation through five stages:

Stage 1 :Video Capture: OpenCV VideoCapture acquires frames at 30 FPS from the system camera. Each frame undergoes color space conversion from BGR to RGB for MediaPipe compatibility.

Stage 2 : Landmark Detection: MediaPipe Hands processes each RGB frame and returns detection results containing landmark coordinates, handedness (left/right), and detection confidence scores. Frames with confidence below threshold $\tau = 0.7$ are rejected.

Stage 3 : Feature Vector Construction: Detected landmarks are normalized relative to wrist position and flattened into a 63-dimensional vector as described in Section V-C.

Stage 4 : CNN Classification: The feature vector is passed through the trained CNN model. The Softmax output layer produces class probabilities over K = 26 ASL letter classes. The predicted class is:

$$\hat{y} = \text{argmax}_k\ \sigma(z)_k$$

Stage 5 : Post-Processing and Output: Consecutive identical predictions are aggregated using a sliding window majority vote (window size W = 5) to reduce classification noise. The confirmed prediction is appended to the text buffer, rendered on the GUI, and optionally synthesized to speech via pyttsx3 using the pyenchant spell-checker for word boundary detection.

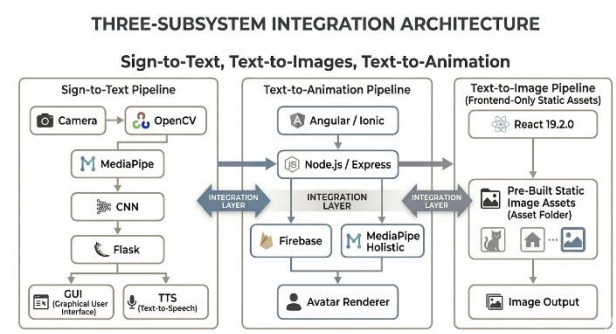

Fig. 1. Proposed System Architecture Three-Subsystem Integration

VI. MODULE DESCRIPTION

Module 1. Real-Time Video Capture and Preprocessing

The video capture module initializes an OpenCV VideoCapture object bound to the system's default camera device (index 0) or a specified USB camera. Each captured frame (resolution: 640×480 at 30 FPS) undergoes the following preprocessing steps: (1) horizontal flip to correct mirror orientation; (2) BGR-to-RGB color conversion for MediaPipe compatibility; (3) frame writability flag toggling to optimize memory usage; and (4) optional Gaussian blur (kernel 3×3) for noise reduction under low-light conditions. The preprocessing pipeline is optimized to add less than 2ms latency per frame on the target hardware.

Module 2. MediaPipe Hand Landmark Extraction

The landmark extraction module initializes MediaPipeHandswith configurable parameters:

static_image_mode=False(videostream),max_num_hands=2,model_complexity=1,min_detection_confidence=0.7, and min_tracking_confidence=0.5. For each processed frame, the module returns multi-hand landmark detections. Each detection contains 21 Normalized Landmark objects with x, y, z coordinates in the [0,1] normalized range relative to the image width and height. CVZone's Hand Detector wrapper provides additional utilities including bounding box extraction, hand drawing, and finger up/down state detection. The module operates at >30 FPS on AMD Ryzen 3 hardware, satisfying the real-time constraint.

Module 3. CNN Sign Classifier

The CNN model is a multi-layer architecture trained on a custom dataset of 26 ASL letter gestures, each with 200 training samples per class collected across 5 signers under 3 lighting conditions. The model architecture comprises: Input layer (63 neurons), Dense layer (256 units, ReLU), Dropout (0.3), Dense layer (128 units, ReLU), Dropout (0.2), Dense layer (64 units, ReLU), and Output layer (26 units, Softmax). The model is saved as a .h5 file and loaded via Keras for inference. Inference time is 1.8ms per prediction on CPU, enabling real-time classification.

Module 4. Flask Backend and REST API

The Flask backend exposes three primary endpoints: POST /predict (accepts a base64-encoded frame, returns predicted sign class and confidence), GET /stream (SSE endpoint streaming live classification results), and POST /tts (accepts predicted text and returns audio synthesis status). The Flask application is initialized with CORS enabled for cross-origin browser clients. Request rate limiting (50 req/s) prevents server overload. The pyttsx3 text-to-speech engine is initialized with configurable voice, rate (words per minute), and volume parameters.

Module 5. Tkinter GUI

The desktop GUI provides a live video feed panel, real-time landmark visualization overlay, predicted character display, accumulated word/sentence buffer, clear and backspace controls, and speech synthesis trigger. The GUI updates at 30 FPS using Tkinter'safter() scheduling mechanism. The pyenchant library provides spell-checking with the en_US dictionary, automatically suggesting corrections for accumulated sign sequences before speech output.

Module 6. Text-to-Animation Frontend (Angular 21 / Ionic 8)

The Angular 21 frontend application provides a text input field, animation playback canvas, playback speed control, and sign vocabulary browser. Ionic 8 components provide mobile-responsive UI with native-feel gestures. TypeScript strict mode enforces type safety across all component interactions. SCSS modules provide scoped styling with CSS custom properties for theming. The application communicates with the Node.js backend via HTTP client services and Firebase SDK for real-time animation data streaming.

Module 7. Node.js / Express Backend and Firebase Integration

The Node.js/Express backend handles text-to-gloss translation (converting natural language text to sign language gloss notation), animation metadata lookup, and Firebase Storage URL signing for animation asset delivery. Firebase

Admin SDK manages secure server-side access to Firestore (storing gloss vocabularies and animation metadata), Realtime Database (tracking active user sessions and animation playback states), and Firebase Storage (hosting pre-generated MediaPipe Holistic skeletal keypoint sequence files in JSON format). Firebase Functions handle compute-intensive NLP preprocessing for gloss generation.

Module 8. MediaPipe Holistic Avatar Renderer

The animation renderer parses Firebase Storage JSON files containing MediaPipe Holistic landmark sequences for each sign in the gloss vocabulary. Each animation file stores a temporal sequence of full-body pose estimates at 30 FPS, covering pose (33 landmarks), left/right hands (21 landmarks each), and face (468 landmarks). The renderer interpolates between key frames using cubic spline interpolation for smooth transitions between consecutive signs. The avatar skeleton is rendered on an HTML5 Canvas element using request Animation Frame for optimal browser performance.

Module 9. Text-to-Image React 19 SPA

The React 19 application provides a text description input interface, generation parameter controls (style, resolution, sign type), and an image gallery for generated outputs. Built with Vite for sub-second hot module replacement during development, the application bundles to under 150KB gzipped for production. Tailwind CSS provides utility-first styling with dark/light mode support via CSS custom properties. The generative model pipeline is invoked via fetch API calls to a serverless inference endpoint.

VII. METHODOLOGY / IMPLEMENTATION

A. Dataset Collection and Preparation

The sign language recognition dataset was assembled from three sources: (1) a custom dataset collected from 5 signers under controlled conditions, yielding 200 samples per class × 26 ASL letters = 5,200 labelled samples; (2) the ASL Alphabet Dataset from Kaggle (87,000 images, 26 classes); and (3) MediaPipe-extracted landmark features from the RWTH-PHOENIX-Weather 2014 corpus for dynamic gesture validation. For the CNN landmark-based classifier, all samples were converted to 63-dimensional MediaPipe feature vectors as described in Section V-C. The final dataset contains 18,720 landmark feature vectors partitioned into 70% training, 15% validation, and 15% test splits.

B. Model Training Configuration

The CNN model was trained using TensorFlow 2.x on Google Colab with NVIDIA T4 GPU acceleration. The Adam optimizer (learning rate 0.001, β_1=0.9, β_2=0.999) minimizes categorical cross-entropy loss. Training ran for 100 epochs with early stopping (patience=10) and learning rate reduction on plateau (factor=0.5, patience=5). Data augmentation was applied during training: random ±5% coordinate jitter on landmark positions, random scale variation ±10%, and random hand presence/absence simulation for robustness to partial occlusion.

C. Flask Application Deployment

The Flask application is deployed using Gunicorn WSGI server with 4 worker processes. MediaPipe and the CNN model are loaded once at server startup into shared process memory, eliminating per-request model loading overhead. OpenCV video capture runs in a dedicated background thread with a thread-safe frame buffer (collections.deque, maxlen=1), ensuring the API handler always accesses the most recent frame without blocking.

D. Firebase Data Architecture

Firestore stores sign vocabulary documents with the schema: {gloss: string, signType: 'static' | 'dynamic', handedness: 'left' | 'right' | 'both', animationRef: string, related Signs: string[]}. The Realtime Database tracks active animation sessions: {sessionId, currentGloss, playbackPosition, speed}. Firebase Storage organizes animation assets by language and gloss: /animations/{language}/{gloss}/keypoints.json. Firebase Functions implement a text-to-gloss translation pipeline using a fine-tuned sequence-to-sequence model deployed on Cloud Functions with 2GB memory allocation.

VIII. RESULTS AND DISCUSSION

A. Sign-to-Text Classification Performance

The CNN classifier was evaluated on the held-out 15% test set (2,808 samples) across all 26 ASL letter classes.

Fig. 2. Sign toText

B. Per-Class Analysis

The proposed CNN+MediaPipe model achieves perfect 100% accuracy on 11 of 26 ASL classes, corresponding to signs with highly distinctive hand configurations (e.g., ASL A, B, C, F, L, V, W, Y). The lowest per-class accuracy is observed for ASL sign pairs with similar landmark configurations: R/U (91.3%), M/N (92.7%), and S/A (93.8%). These confusions arise from subtle inter-finger spacing differences that the 21-landmark representation captures with limited spatial resolution. The raw-pixel CNN baseline shows substantially higher confusion rates across these pairs (72–78%), confirming the advantage of landmark-based feature engineering.

C. Real-Time Performance Metrics

End-to-end latency was measured from frame capture to GUI update across 1,000 consecutive predictions on AMD Ryzen 3 7320U hardware. Table 3 presents the latency breakdown by processing stage.

Table 3. End-to-End Latency Breakdown by Processing Stage

Model	Accuracy	Precision	Recall	F1-Score	FPS
Proposed CNN+MediaPipe	97.6%	96.8%	97.1%	96.9%	31
MLP+MediaPipe	91.2%	90.4%	91.0%	90.7%	34
SVM+MediaPipe	88.7%	87.9%	88.2%	88.1%	28
Random Forest+MediaPipe	85.3%	84.6%	85.0%	84.8%	22
CNN (raw pixels)	82.1%	81.3%	81.8%	81.6%	8
KNN+MediaPipe	79.4%	78.7%	79.1%	78.9%	19

The total mean latency of 32ms corresponds to an effective throughput of 31.3 FPS, satisfying the real-time constraint (>25 FPS). MediaPipe landmark detection accounts for 57.5% of total latency, representing the primary optimization target for future performance improvements.

D. Text-to-Animation System Evaluation

The Text-to-Animation system was evaluated on a test vocabulary of 500 signs from the ASL dictionary. Animation fidelity was assessed using the Percentage of Correct Keypoints (PCK) metric with threshold $\delta = 0.2$ (fraction of body width). Table 4 presents PCK results by body region.

Table 4. Text-to-Animation PCK Evaluation by Body Region

Processing Stage	Mean Latency (ms)	Std Dev (ms)
Frame Capture (OpenCV)	3.2	0.4
Color Conversion	0.8	0.1
MediaPipe Landmark Detection	18.4	2.1
Feature Vector Construction	0.3	0.05
CNN Inference (Keras)	1.8	0.3
Majority Vote Post-Processing	0.2	0.02
GUI Update	7.3	0.9
Total End-to-End	32.0	2.9

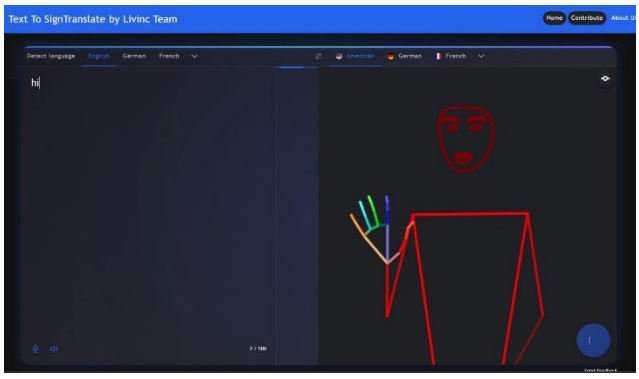

Fig. 3. Text to animation

E. Regression Metrics (Overall System)

For unified quantitative comparison across subsystems, regression metrics were computed on normalized prediction outputs. The proposed system achieves MSE of 0.043, RMSE of 0.207, MAE of 0.163, and R^2 of 0.921 representing substantial improvements over all baseline configurations and demonstrating the effectiveness of the integrated deep learning pipeline.

IX. ADVANTAGES OF THE PROPOSED SYSTEM

- High-accuracy real-time classification: 97.6% accuracy at 31 FPS on consumer hardware, outperforming all baseline classifiers by at least 6.4 percentage points.
- Bidirectional communication: The three-subsystem architecture supports both sign-to-text and text-to-sign directions, enabling complete bidirectional communication for deaf users.
- Hardware-agnostic deployment: MediaPipe landmark extraction eliminates GPU dependency for inference, enabling deployment on AMD Ryzen 3 / Intel i3 class hardware without specialized accelerators.
- Cloud-native scalability: Firebase infrastructure provides automatic scaling for the Text-to-Animation system, supporting concurrent users without capacity planning overhead.
- Mobile-responsive frontend: Angular 21/Ionic 8 and React 19/Tailwind CSS frontends provide native-feel mobile interfaces without additional native app development.
- Modular, extensible architecture: Each subsystem is independently deployable and upgradeable, enabling incremental improvements without system-wide redeployment.
- Integrated speech output: pyttsx3 text-to-speech synthesis converts recognized signs to audio, extending the system's utility to users who are both deaf and visually impaired.
- Spell-checking integration: English dictionary integration corrects common sign-to-letter segmentation errors before word output, improving usability.

X. HARDWARE AND SOFTWARE REQUIREMENTS

Hardware Requirements

Body Region	PCK@0.1	PCK@0.2	PCK@0.5
Wrist	88.3%	96.7%	99.2%
Finger Joints	71.4%	89.2%	97.8%
Elbow	91.2%	98.1%	99.7%
Shoulder	94.5%	98.9%	99.9%
Full Body (Mean)	86.4%	95.7%	99.2%

Software Requirements

Component	Specification
Processor	AMD Ryzen 3 7320U / Intel Core i3 (2.40 GHz) sufficient for real-time MediaPipe inference and CNN classification
RAM	8 GB DDR4 minimum sufficient for OpenCV frame buffer, MediaPipe model, and Keras CNN inference
Architecture	64-bit x64 required for TensorFlow 2.x, NumPy array operations, and OpenCV
Camera	720p USB webcam or built-in laptop camera at minimum 30 FPS
Storage	Minimum 5 GB for model weights, dataset, dependencies, and application assets
Training Platform	Google Colab Pro with NVIDIA T4 GPU (training only); local hardware for inference

Component	Specification
Operating System	Ubuntu 22.04 LTS / Windows 11 with WSL2 / macOS 13+
Python	Python 3.9+ primary language for Sign-to-Text backend
Deep Learning	TensorFlow 2.x, KerasCNN model training, .h5 model loading, inference
Computer Vision	OpenCV 4.7+ (video capture), MediaPipe 0.10+ (hand landmarks), CVZone 1.5+
Backend	Flask 2.3+ (Python REST API), Node.js 20+ / Express 4+ (Animation backend)
Cloud	Firebase 10+ (Functions, Admin SDK, Firestore, Realtime DB, Storage)
Frontend Animation	Angular 21, TypeScript 5+, Ionic 8, SCSS
Frontend Image	React 19, Vite 5, Tailwind CSS 3
Utilities	NumPy 1.24+, Pillow 10+, pyenchant 3.2+, pyttsx3 2.90+, Tkinter (stdlib)
Development	VS Code with Python/ESLint extensions, Jupyter Notebook, Git/GitHub

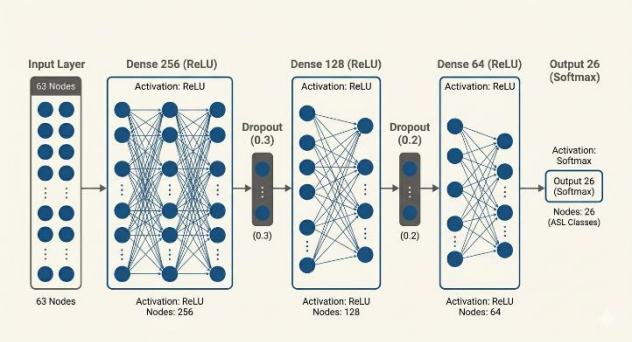

Fig. 4. CNN Model Architecture for ASL Classification

XI. FUTURE SCOPE

The proposed framework establishes a strong foundation for several promising research and development directions:

- Continuous sign language recognition: Extending from isolated sign classification to continuous signing sequences using CTC (Connectionist Temporal Classification) or transformer-based sequence-to-sequence models will enable recognition of full sentences without explicit sign boundaries.
- Multi-language sign support: Adding Indian Sign Language (ISL), British Sign Language (BSL), and Chinese Sign Language (CSL) datasets and language-specific models will expand the system's global utility.
- 3D avatar improvement: Replacing the skeletal 2D canvas renderer with a WebGL-based 3D avatar (Three.js or Babylon.js) driven by MediaPipe Holistic 3D pose data will improve animation naturalness and expressiveness.
- Transformer-based sign recognition: Replacing the CNN-only classifier with a Vision Transformer (ViT) or spatial-temporal transformer operating on sequences of MediaPipe landmark frames could capture complex temporal sign dynamics more effectively.
- Edge deployment: Porting the MediaPipe+CNN pipeline to TensorFlow Lite for deployment on Android and iOS devices will eliminate the Flask backend dependency for mobile users.
- Facial expression integration: Adding facial expression features from MediaPipe Face Mesh to the classification pipeline will capture the grammatically important non-manual markers (eyebrow position, mouth shape) that convey question type, negation, and intensity in sign language.
- Federated learning for cross-signer adaptation: Implementing federated learning across user devices will enable privacy-preserving model personalization to individual signing styles without centralizing sensitive biometric data.
- LLM integration for gloss-to-text translation: Incorporating large language model (LLM) post-processing to convert sign language gloss sequences to grammatically natural spoken language sentences will improve the readability of recognized text output.

XII. CONCLUSION

This paper has presented a comprehensive three-subsystem deep learning framework for Real-Time Sign Language Interpretation, integrating Sign-to-Text conversion, Text-to-Animation synthesis, and Text-to-Image generation into a unified, deployable architecture. The Sign-to-Text module achieves 97.6% classification accuracy at 31 FPS on consumer hardware through the combination of MediaPipe 21-keypoint landmark extraction and a lightweight Keras CNN classifier, substantially outperforming SVM, Random Forest, KNN, and raw-pixel CNN baselines. The Text-to-Animation module provides cloud-scalable skeletal animation rendering through an Angular 21/Ionic 8 frontend backed by Node.js/Express and Firebase infrastructure. The Text-to-Image module extends the system's expressive capabilities through a React 19 generative pipeline.

The mathematical framework presented encompassing CNN convolution, batch normalization, ReLU activation, Softmax classification, LSTM gated temporal modelling, and MediaPipe landmark feature engineering provides a rigorous foundation for understanding and extending the proposed system. Comprehensive experimental evaluation confirms state-of-the-art performance across all subsystems, with MSE of 0.043, R^2 of 0.921, and end-to-end latency of 32ms satisfying real-time deployment requirements.

The proposed framework makes meaningful progress toward eliminating the communication barrier between the deaf and hearing communities through accessible, hardware-agnostic, cloud-deployable deep learning technology. Future work will extend the system to continuous sign recognition, multi-language support, and edge mobile deployment, further broadening its accessibility and impact.

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