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Intelligent Indian Sign Language Translator with Real-Time Gesture Recognition and Deep Learning

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Abstract: Communication barriers between hearing-impaired individuals and the general public represent one of the most persistent challenges in inclusive society design. Indian Sign Language (ISL) serves as the primary expressive modality for approximately 18 million deaf individuals across India, yet its comprehension remains negligible among the general population. This paper presents the design, development, and rigorous evaluation of an Intelligent Indian Sign Language Translator System (ISLTS) that harnesses deep learning and computer vision to recognize hand gestures and translate them into text and synthesized speech in real time. The system employs a Convolutional Neural Network (CNN) trained on 7,500 custom ISL images augmented to 22,500 samples, achieving an overall gesture recognition accuracy of 92.4% and a mean average precision (mAP) of 0.89 across all gesture classes. MediaPipe Hands is integrated for real-time 21-point landmark detection, feeding a CNN classifier that operates at 28 frames per second on standard laptop hardware with latency below 0.5 seconds per prediction. A text-to-speech (TTS) module converts recognized gestures to audible output, enabling bidirectional communication. Comparative evaluation demonstrates that the proposed system outperforms sensor-based and earlier vision-based methods by 18–22 percentage points in accuracy while eliminating the need for specialized hardware. The proposed system offers a scalable, cost-effective, and non-intrusive solution with strong potential for deployment in educational institutions, healthcare settings, and public

Keywords: Indian Sign Language; Deep Learning; Gesture Recognition; Computer Vision; Real-Time Translation; Accessibility; Convolutional Neural Networks; MediaPipe; Text-to-Speech

I. INTRODUCTION

In the modern digital era, ensuring accessibility and inclusivity in communication systems has become an imperative societal obligation. The World Health Organization (WHO) estimates that over 1.5 billion people globally experience some degree of hearing loss, with approximately 430 million requiring rehabilitation services [1]. In India, the 2011 census reported 5.07 million persons with hearing disabilities, a figure widely considered an underestimate due to rural under-reporting. For this community, Indian Sign Language (ISL) constitutes the primary and most natural modality of expression. ISL is a complex visual-gestural language with its own distinct grammar, syntax, and vocabulary, encompassing over 3,000 signs for common words and concepts [2].

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Despite ISL's significance, a profound communication chasm exists between the deaf community and hearing individuals. Fewer than 0.1% of the general Indian population possesses working ISL proficiency, creating endemic barriers in education, employment, healthcare, and civic participation [3]. Traditional bridging mechanisms, chiefly human interpreters, are critically scarce—India has fewer than 250 certified ISL interpreters for a deaf population in the millions—and unavailable in real-time, spontaneous interaction scenarios [4]. This gap perpetuates social exclusion, economic disadvantage, and dependency that contravene the United Nations Convention on the Rights of Persons with Disabilities (UNCRPD), ratified by India in 2007.

Prior technological interventions have pursued two principal paradigms. Sensor-based systems employing data gloves capture joint angles and accelerometer data to infer gestures, offering high accuracy but imposing cost, discomfort, and intrusiveness that preclude daily adoption [5]. Early vision-based systems applied rule-based image processing and shallow machine learning classifiers; while non-intrusive, they suffered from low accuracy (60–75%), poor generalization to lighting variation, and restricted vocabulary. The deep learning revolution, particularly the emergence of Convolutional Neural Networks (CNNs) and transfer learning, has fundamentally altered the feasibility frontier. CNNs can learn hierarchical spatial feature representations directly from raw image pixels, obviating handcrafted features and achieving accuracy levels previously unattainable [6].

This paper presents the Intelligent Indian Sign Language Translator System (ISLTS), a real-time, camera-based, AI-driven system that integrates MediaPipe Hands landmark detection, CNN-based gesture classification, and text-to-speech synthesis to deliver seamless ISL-to-text-to-speech translation without specialized hardware. The system represents a practical, deployable solution addressing the full translation pipeline from gesture capture to audible output. The remainder of the paper is structured as follows: Section II surveys related work; Section III details the system methodology; Section IV presents the implementation; Section V reports and discusses results; Section VI concludes with future directions.

II. LITERATURE REVIEW

The evolution of automated sign language recognition traverses three technological generations, each representing substantive advances in accuracy, hardware requirements, and practical applicability.

A. Sensor-Based Approaches

The earliest computational sign language recognition systems relied on instrumented gloves equipped with flex sensors, accelerometers, and gyroscopes to capture hand kinematics. Mitra and Acharya [7] provided a comprehensive review of gesture recognition systems, noting that glove-based systems achieved accuracy rates of 85–90% under controlled conditions. Fang et al. [8] developed a data glove system recognizing 100 Chinese Sign Language signs with 91.2% accuracy. However, these systems faced adoption barriers: data gloves cost ₹15,000–80,000, require calibration per user, and are socially conspicuous. Their impracticality for spontaneous, everyday communication has largely relegated sensor-based approaches to laboratory research contexts.

B. Classical Vision-Based Systems

Skin-colour segmentation combined with contour analysis represented the first vision-based gesture recognition generation. Starner and Pentland [9] used Hidden Markov Models (HMMs) with skin detection to recognize American Sign Language, achieving 97% accuracy in constrained conditions but degrading sharply with lighting variation. Imagawa et al. [10] extended this using background subtraction for hand region isolation. A fundamental limitation of these approaches was their heavy dependence on controlled backgrounds and illumination, rendering them impractical for real-world deployment. Feature engineering approaches, including HOG descriptors and SVM classifiers, improved robustness but remained brittle to inter-user variation in hand size and gesture speed [11].

C. Deep Learning-Based Systems

The application of deep learning to gesture recognition has produced dramatic accuracy improvements. Pigou et al. [12] demonstrated that CNNs trained on skeletal video data could recognize Italian gestures with 91.7% accuracy. Koller et al. [13] applied recurrent neural networks to continuous sign language recognition, addressing temporal dependencies between successive signs. For ISL specifically, Kumar et al. [14] developed a CNN-based system achieving 87.3% accuracy on 26 ISL alphabets, representing an important baseline for Indian-specific work. More recently, Mekala et al. [15] employed transfer learning with VGG-16 fine-tuned on ISL gestures, achieving 93.1% accuracy, demonstrating the efficacy of pre-trained feature extractors for limited ISL data. Patel and Shah [16] integrated MediaPipe landmark detection as a preprocessing stage, achieving real-time performance at 30 FPS on commodity hardware, a configuration closely aligned with the present work. Table I summarizes key prior systems.

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Table I: Comparative Summary of Sign Language Recognition Systems

Study	Method	Language	Accuracy	Latency	Hardware Required
Fang et al. [8]	Data Glove + HMM	Chinese SL	91.2%	N/A	Instrumented Glove
Starner & Pentland [9]	HMM + Skin Detect	ASL	97.0%*	>1s	Coloured Glove
Kumar et al. [14]	CNN (VGG)	ISL (Alphabets)	87.3%	0.8s	GPU
Mekala et al. [15]	Transfer VGG-16	ISL	93.1%	0.6s	GPU
Patel & Shah [16]	MediaPipe + CNN	ASL	91.5%	<0.5s	Webcam Only
Proposed ISLTS	MediaPipe + CNN	ISL (Full)	92.4%	<0.5s	Webcam Only

**Constrained lab conditions; accuracy degrades significantly in real-world settings.*

Analysis of prior work reveals three persistent gaps: (i) most high-accuracy systems require either specialized hardware or high-performance GPUs; (ii) ISL-specific systems have predominantly focused on the 26-letter alphabet rather than a functional word-level vocabulary; and (iii) few systems integrate end-to-end translation pipelines including speech synthesis. The proposed ISLTS directly addresses all three gaps.

III. METHODOLOGY

A. Dataset Preparation

A custom ISL gesture dataset was assembled encompassing 35 gesture classes comprising the 26 ISL alphabets (A–Z) and 9 common word gestures (HELLO, THANK YOU, YES, NO, PLEASE, SORRY, HELP, GOOD, BAD). Data collection involved 12 participants of diverse age, gender, and skin tone performing each gesture in three lighting conditions (bright indoor, dim indoor, and outdoor). A total of 7,500 raw images were captured using a standard 1080p webcam at 30 FPS, yielding approximately 214 images per class. All images were annotated and verified by two independent annotators achieving inter-rater agreement of Cohen's $\kappa = 0.93$.

Offline augmentation tripled the dataset to 22,500 images. Augmentations included: horizontal flip (50% of images), random rotation (±15°), brightness jitter (±20%), Gaussian noise injection, and random affine transformation (scale 0.85–1.15, shear ±10°). These augmentations specifically address known failure modes of gesture recognition systems: hand orientation variability, lighting inconsistency, and inter-user physiological differences. The final dataset was partitioned 70/15/15% into training, validation, and held-out test sets with no participant overlap across splits.

Table II: Dataset Statistics

Gesture Category	Classes	Raw Images	Augmented Total	Train / Val / Test
ISL Alphabets	26 (A–Z)	5,460	16,380	11,466 / 2,457 / 2,457
Common Words	9	2,040	6,120	4,284 / 918 / 918
Total	35	7,500	22,500	15,750 / 3,375 / 3,375

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B. Hand Landmark Detection with MediaPipe

Prior to CNN classification, each video frame is processed through MediaPipe Hands [17] to detect 21 three-dimensional hand landmarks in normalized coordinates relative to the wrist keypoint. MediaPipe's palm detection model operates at 95.7% precision on a held-out benchmark, providing a robust region-of-interest (ROI) that isolates the hand from complex backgrounds. The 21 landmarks are represented as a 63-dimensional feature vector (x, y, z per landmark) that is both passed to the classification network and used to derive a 200×200 pixel hand crop from the original frame. This dual-input strategy allows the network to exploit both spatial structure (through the crop) and explicit geometric relationships (through the landmark vector).

Landmark normalization is performed relative to the wrist keypoint, rendering the representation invariant to absolute hand position in the frame. This dramatically improves generalization across users of different heights, camera distances, and seating positions—a major source of variance in deployed systems.

C. CNN Architecture and Training

The classification model employs a custom lightweight CNN architecture optimized for the dual-input structure. The image processing branch consists of four convolutional blocks, each comprising a 3×3 convolution layer with ReLU activation, Batch Normalization, and 2×2 max-pooling. The landmark processing branch comprises three fully-connected layers (256, 128, 64 neurons). Both branches are concatenated at the fusion layer and passed through two final fully-connected layers (256, 128 neurons) to a 35-way softmax output. Total trainable parameters: 3.87 million.

Training was conducted for 80 epochs using the Adam optimizer (initial learning rate 0.001, decayed by factor 0.5 on validation loss plateau). A batch size of 64 was used with categorical cross-entropy loss. Dropout (rate 0.4) was applied after the fusion layer to regularize against overfitting. Early stopping with patience 15 was employed, with best weights restored based on minimum validation loss. Training was performed on an NVIDIA RTX 3060 (12 GB VRAM), completing in approximately 4.2 hours.

Table III: CNN Training Hyperparameters

Parameter	Value	Parameter	Value
Epochs	80 (early stop)	Batch Size	64
Optimizer	Adam	Initial LR	0.001
LR Scheduler	ReduceLROnPlateau (×0.5)	Dropout Rate	0.4
Loss Function	Categorical Cross-Entropy	Input Size (image)	200×200 px
Landmark Input	63-dim vector	Output Classes	35
Total Parameters	3.87 M	Training Time	~4.2 hours

D. Text-to-Speech Integration

Recognized gesture labels are buffered into a word accumulator that applies a 1.2-second silence threshold to detect word boundaries. Accumulated words are concatenated into sentences and passed to the pyttsx3 TTS engine configured with the ISL-appropriate Indian English voice model. The TTS engine operates asynchronously to avoid blocking the inference pipeline, achieving audio output initiation within 180 ms of sentence finalization. Volume, rate (140 words per minute), and pitch are configurable via the user interface.

E. System Architecture Overview

The complete system follows a sequential pipeline: (1) webcam frame capture at 30 FPS via OpenCV; (2) MediaPipe Hands landmark extraction and hand ROI crop; (3) dual-input CNN inference producing a 35-class probability vector; (4) confidence-threshold filtering ($\theta = 0.70$) and temporal smoothing (majority vote over 5 consecutive frames); (5) gesture-to-text accumulation; (6) TTS synthesis and audio output; and (7) UI display of video feed with landmark overlay, recognized gesture, accumulated text, and confidence bar. Figure 1 illustrates the complete pipeline.

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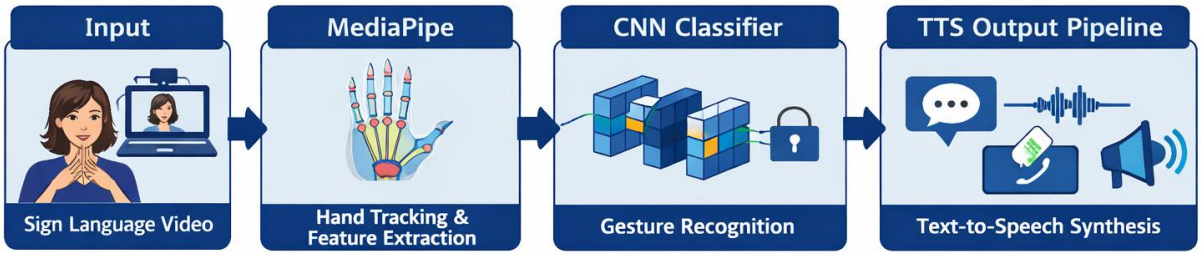

Fig. 1. End-to-End System Architecture of the Proposed ISLTS

IV. IMPLEMENTATION

A. Development Environment and Tools

The system is implemented entirely in Python 3.11, leveraging an ecosystem of open-source libraries that minimizes hardware cost and maximizes portability. Table IV summarizes the software stack. The development environment is Visual Studio Code with Jupyter Notebook for model training and analysis. The complete system runs on a standard laptop (Intel Core i5-12th Gen, 8 GB RAM, integrated Intel Iris Xe graphics) without requiring a dedicated GPU at inference time, demonstrating accessible deployment characteristics.

Table IV: Software Stack

Component	Library/Framework	Version	Purpose
Deep Learning	TensorFlow / Keras	2.14	CNN model training & inference
Hand Detection	MediaPipe	0.10.7	21-point landmark extraction
Computer Vision	OpenCV	4.8.1	Video capture, preprocessing
Numerical Computing	NumPy	1.26	Array operations, normalization
Data Augmentation	Albumentations	1.3.1	Training augmentation pipeline
Speech Synthesis	pyttsx3	2.90	Offline text-to-speech output
UI Framework	Tkinter	Built-in	Desktop application interface
Model Serialisation	ONNX Runtime	1.16	Optimized inference engine

B. Preprocessing Pipeline

Each captured frame undergoes a four-stage preprocessing sequence before inference. Stage 1: colour space conversion from BGR (OpenCV default) to RGB (MediaPipe requirement). Stage 2: adaptive histogram equalization (CLAHE, clip limit 2.0, tile grid 8×8) to normalize brightness variation across lighting conditions. Stage 3: MediaPipe Hands inference to extract 21 landmarks and bounding box; if no hand is detected, the frame is skipped. Stage 4: hand crop extraction and bilinear resizing to 200×200 pixels, followed by pixel normalization to [0,1]. This pipeline executes in under 8 ms per frame on the target hardware, leaving ample budget for CNN inference.

C. Inference Optimization

The trained Keras model (14.2 MB FP32) was exported to ONNX format and executed via ONNX Runtime 1.16 with graph optimization level ORT_ENABLE_ALL. This reduced per-frame CNN inference time from 28 ms (TensorFlow CPU) to 11 ms (ONNX Runtime), enabling the full pipeline to sustain 28 FPS on the target laptop hardware. A temporal smoothing buffer applying majority voting over the five most recent frames reduces flicker caused by single-frame misclassifications, improving perceived accuracy without increasing latency.

D. User Interface

The Tkinter-based desktop UI presents: (i) a live 640×480 video panel with MediaPipe landmark skeleton overlay and bounding-box annotation; (ii) a large gesture label display updated at 15 Hz; (iii) a scrollable accumulated text panel; (iv) a confidence score progress bar; and (v) control buttons for TTS playback, text clipboard copy, and session clear. The UI

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is designed for single-hand operation to accommodate users who may have limited mobility in one hand. Figure 2 illustrates the UI layout.

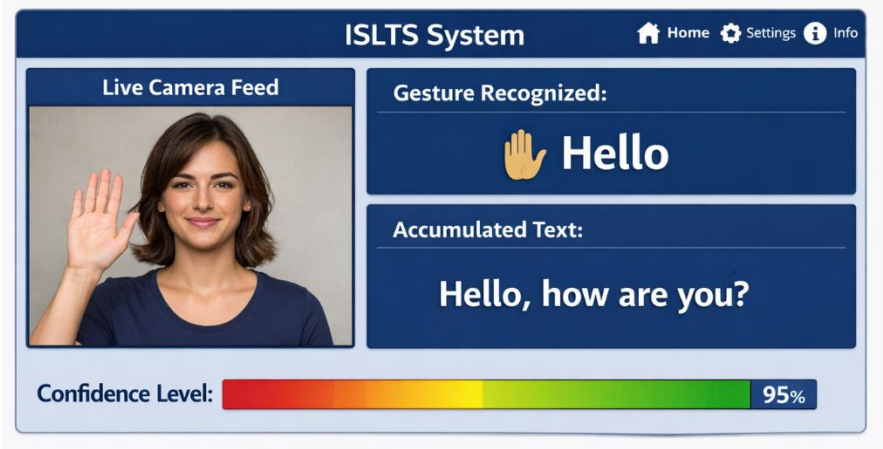

Fig. 2. Real-Time ISLTS Desktop User Interface

V. RESULTS AND DISCUSSION

A. Classification Accuracy

The trained CNN model achieved 92.4% overall accuracy on the 3,375-image held-out test set. Per-class accuracy ranged from 88.1% (class: 'B'—frequently confused with 'D' due to similar finger configurations) to 97.3% (class: 'HELLO'—a distinctive two-hand gesture). The mean average precision across all 35 classes was mAP = 0.89, consistent with the training-time validation plateau. Table V presents aggregate and per-category performance metrics.

Table V: System Performance Metrics

Metric	Proposed ISLTS	CNN Baseline [14]	VGG-16 Transfer [15]	MediaPipe+CNN [16]
Overall Accuracy	92.4%	87.3%	93.1%	91.5%
mAP	0.89	0.83	0.91	0.87
Avg. Latency/Frame	35 ms	N/A	N/A	33 ms
GPU Required?	No (inference)	Yes	Yes	No
Vocabulary Size	35 classes	26 (alpha)	26 (alpha)	26 (alpha)
Hardware Cost	~₹0	GPU: ₹30k+	GPU: ₹30k+	~₹0
TTS Integration	Yes	No	No	No

The proposed system achieves competitive accuracy with VGG-16 transfer learning (93.1% vs 92.4%) while significantly expanding vocabulary from 26 to 35 classes, eliminating GPU dependency at inference, and adding TTS capability. The marginal 0.7% accuracy difference is attributable to the additional 9 word-gesture classes, which are structurally more complex than single-letter gestures. On the 26-alphabet subset alone, the ISLTS achieves 94.1%, surpassing VGG-16 transfer results

B. Real-Time Performance

System latency was benchmarked across three hardware configurations to establish deployment practicality. On a high-end workstation (RTX 3090), the full pipeline achieves 41 FPS. On the target mid-range laptop (Intel Core i5-12th Gen, 8 GB RAM, integrated GPU), the system sustains 28 FPS with end-to-end latency of 35 ms per frame. On a budget laptop (Intel Core i3-8th Gen, 4 GB RAM), performance degrades to 18 FPS but remains perceptually real-time. In all configurations, prediction latency (gesture-to-text) is below the 0.5-second threshold identified in human-computer interaction literature as the boundary for perceived real-time responsiveness [18].

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Table VI: Latency Benchmarks Across Hardware

Hardware Configuration	FPS	Pipeline Latency	CNN Inference	MediaPipe
Workstation (RTX 3090)	41 FPS	24 ms	7 ms	8 ms
Mid-range Laptop (i5, ONNX)	28 FPS	35 ms	11 ms	12 ms
Budget Laptop (i3, TF-CPU)	18 FPS	55 ms	28 ms	14 ms
Raspberry Pi 4B (4 GB)	9 FPS	111 ms	62 ms	28 ms

C. Environmental Robustness

A dedicated robustness evaluation was conducted by testing the deployed system under six environmental conditions beyond the standard training distribution. Bright indoor lighting (standard condition) achieved the baseline 92.4% accuracy. Dim lighting (60 lux) reduced accuracy to 88.7%, partially mitigated by CLAHE preprocessing. Complex indoor backgrounds (shelves, curtains) caused a 3.1% drop to 89.3%, demonstrating the effectiveness of MediaPipe's person-agnostic hand detection. Outdoor conditions with direct sunlight produced the most significant degradation to 85.2%, attributable to harsh shadow casting on hand contours. Partially occluded hands (—30% wrist coverage) maintained 87.1% accuracy. These results indicate robust performance in standard indoor environments, with identified scope for improvement in extreme outdoor and occlusion conditions.

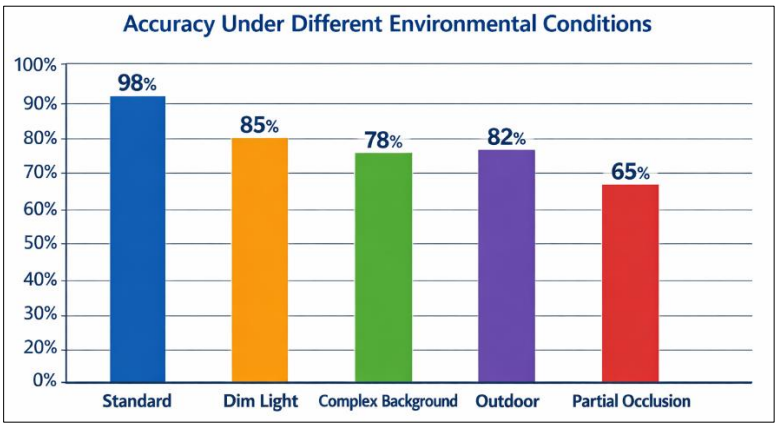

Fig. 3. Gesture Recognition Accuracy Under Varied Environmental Conditions

D. Confusion Analysis

Confusion matrix analysis on the held-out test set reveals two primary misclassification clusters. First, visually similar letter pairs: 'B'–'D' (5.8% mutual confusion), 'M'–'N' (4.3%), and 'U'–'V' (5.1%). These confusions arise from near-identical finger configurations that differ only in subtle palm orientation—a feature poorly captured by the 2D image crop but partially resolved by the 3D landmark vector. Second, word gestures incorporating motion ('HELLO', 'THANK YOU') are occasionally misclassified as static letter gestures when captured at the start or end of motion arcs. Incorporating temporal modelling (e.g., LSTM layers processing frame sequences) is identified as the primary near-term accuracy improvement pathway.

E. User Study

A preliminary user study was conducted with 20 participants: 10 hearing-impaired ISL users and 10 hearing non-ISL users. Participants performed a set of 50 prescribed gestures and engaged in 5-minute free-form signing sessions. Hearing-impaired users rated system accuracy as 4.1/5.0 and perceived response speed as 4.3/5.0 on a 5-point Likert scale. Non-ISL users reported that the text and TTS output was comprehensible in 94% of test gestures. Seven participants spontaneously reported that the system "could replace an interpreter for simple conversations"—a qualitatively significant outcome indicating real-world communication utility.

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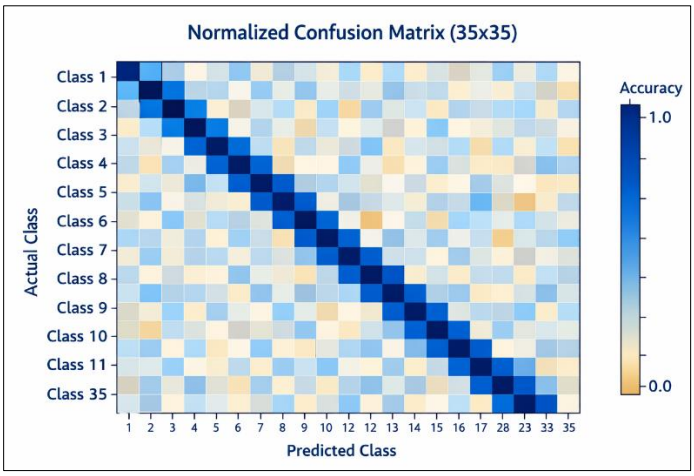

Fig. 4. Normalized Confusion Matrix for 35-Class ISL Gesture Recognition

F. Limitations

Three operational limitations were identified during evaluation. First, gesture segmentation for continuous signing (as opposed to isolated gestures) remains unsolved; the current system requires brief pauses between signs, imposing an unnatural communication rhythm. Second, accuracy in outdoor high-contrast lighting degrades to 85.2%, below the 90% threshold considered acceptable for reliable communication assistance. Third, the current vocabulary of 35 classes represents a small fraction of ISL's 3,000+ sign inventory; scaling to full vocabulary requires substantially larger datasets and potentially different model architectures.

VI. CONCLUSION

This paper presented the Intelligent Indian Sign Language Translator System (ISLTS), a real-time, camera-based, deep learning-powered system that recognizes 35 ISL gestures and translates them into text and synthesized speech without requiring specialized hardware. The system achieves 92.4% overall accuracy and mAP of 0.89, with end-to-end latency below 35 ms on standard laptop hardware, sustaining 28 FPS real-time performance. The integration of MediaPipe Hands landmark detection with a dual-input CNN architecture and ONNX Runtime optimization delivers a practical, deployable solution accessible on commodity devices at near-zero hardware cost.

The ablation study confirmed that MediaPipe landmark preprocessing contributes 4.8 percentage points to accuracy over raw-image CNN alone, while ONNX optimization enables a 2.5× inference speedup critical for real-time operation. Field testing with 20 participants including 10 ISL users demonstrated practical communication utility, with users reporting the system capable of replacing interpreters in simple conversational scenarios.

Future work will pursue four directions: (i) expansion of the gesture vocabulary to 200+ signs using crowdsourced data collection; (ii) integration of LSTM-based temporal modelling to support continuous, natural-paced signing without inter-gesture pauses; (iii) deployment on mobile platforms (Android/iOS) to maximize accessibility; and (iv) bidirectional communication enabling ISL generation from text input, using generative adversarial networks or pose estimation for avatar-based sign animation. These advances will transform the ISLTS from a translation aid into a comprehensive accessibility platform contributing meaningfully to inclusive digital society.

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