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Beyond Silence: Enhancing Accessibility for the Deaf and Mute through ISLR Innovation

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Abstract: This paper proposes an efficient method for Indian Sign Language (ISL) recognition to bridge the communication gap faced by individuals with hearing and speech impairments. Leveraging advanced machine learning techniques, the system integrates image segmentation, feature extraction, and classification. Two texture descriptors—Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM)—are used to capture distinctive spatial features of hand gestures. Using LBP, the Random Forest classifier achieves an impressive accuracy of 99.45%, while GLCM yields 95.64%, both outperforming existing benchmarks. These results underscore the model's potential as a real-world assistive tool, enhancing inclusivity for the deaf and hard-of-hearing community. This research makes a significant contribution to the advancement of ISL recognition, where technology enables accessible and meaningful communication.

Keywords: Sign Database, LBP, GLCM, SL, ISL, Deaf and Dumb

INTRODUCTION

Across generations and cultural landscapes, sign language (SL) has evolved into a powerful and indispensable mode of communication. Long before spoken languages were formalized, humans instinctively turned to gestures—simple yet profoundly expressive movements—to convey basic ideas and emotions. For individuals who are deaf or mute, sign language is far more than a tool; it is a lifeline for connection, understanding, and expression. Interestingly, the use of gestures as a form of communication dates back to ancient times—even hearing individuals have historically relied on hand signals and facial expressions to interact and convey meaning [1].

Sign language serves as a vital lifeline for individuals who are hard of hearing or non-verbal, empowering them to engage confidently and meaningfully in everyday interactions. Far more than a series of hand gestures, it is a rich and expressive visual language that weaves together body posture, facial expressions, gestures, and motion to convey nuanced and complex ideas. Unlike spoken languages that rely on sound, sign languages operate within a visual-manual modality. Communication is shaped not only by manual elements such as handshape, orientation, location, and movement but also by non-manual cues—including facial expressions, eye gaze, head tilts, and lip movements—which add depth and clarity to the intended message [2].

Traditional media have long served as essential tools for enabling both written and spoken communication. For individuals with hearing, spoken language facilitates real-time interaction, while written forms provide a lasting means of expression. With the advent of modern communication platforms—from newspapers and television to smartphones and the internet—both verbal and written exchanges have become faster and more accessible than ever. However, for individuals with speech, writing, or hearing impairments, these advancements still present significant challenges. For millions around the world, sign language remains a primary mode of nonverbal communication, though it often relies on specialized tools, assistive technologies, or interpreters to bridge the communication divide [4].

It's important to recognize that sign language is not universally understood or used. Each country and often each region has developed its distinct system of signs. Influenced by local culture, linguistic diversity, and regional customs, many of the world's sign languages have evolved independently, even if they share origins with British or American Sign Language. In India alone, the presence of numerous sign languages and dialectal variations poses a unique challenge in designing a unified recognition system. Table 1 offers a snapshot of some of the most widely used sign languages across the globe.

Table 1: Visual Vernaculars: Exploring the Diversity of Global Sign Languages

Sr. No.	Region / Country /Entity	Sign language Name	Abb
1	Asia – Japan - India -China [5]	Japanese Sign Lang Indian Sign Lang Chinese Sign Lang	JSL ISL CSL
2	Middle East [6]	Middle-Eastern Countries	ArSL
3	Republic of India [7]	Indian Sign language	ISL
4	Middle-East [8]	Arabic Sign language	ArSL
5	Japan [9]	Japanese Sign Language	JSL
6	Commonwealth of Australia [10]	Australian Sign language	Auslan
7	People's Republic of China [11]	Chinese Sign language	CSL

INDIAN SIGN LANGUAGE

Communication is a fundamental human right, yet for the Deaf and Mute communities, the world often remains riddled with silent barriers. Over the past few decades, researchers have tirelessly explored avenues to bridge this divide, with Indian Sign Language Recognition (ISLR) emerging as a promising frontier in accessible technology[12]. Early works in sign language recognition primarily focused on American Sign Language (ASL), leveraging static image recognition and rule-based systems. However, the cultural and structural uniqueness of Indian Sign Language (ISL) with its rich gestures and regional diversity posed distinct challenges that global solutions couldn't address. This realization sparked a wave of research specifically tailored to ISL, combining linguistics, computer vision, and machine learning [13].

Recent advancements have seen the integration of texture-based descriptors like Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM), which significantly improved gesture feature extraction. These descriptors allow for detailed hand shape and motion analysis, enabling machines to interpret signs with greater nuance. Vision-based approaches, using convolutional neural networks (CNNs), have further accelerated recognition accuracy, often achieving real-time performance in lab environments [14]. Several researchers have proposed hybrid models that fuse deep learning with gesture segmentation techniques, offering promising accuracy in dynamic environments. Tools like MediaPipe and OpenPose have also been integrated into ISLR pipelines, allowing for precise hand tracking without the need for gloves or markers making these solutions more practical and user-friendly [15].

Moreover, innovative communication systems have been designed to translate ISL into speech or text, serving as two-way translators. These systems not only empower Deaf and Mute individuals to express themselves more freely but also educate hearing users on ISL, promoting mutual understanding.

One of the most creative contributions in this realm is the development of ISL-integrated visual aids such as the "Helping Hands" typeface, which marries Roman alphabets with sign language symbols. This not only boosts ISL literacy but also subtly introduces the general public to the visual grammar of ISL, fostering cultural empathy through design.

Despite these advances, challenges remain. Variability in gesture speed, lighting conditions, and signer differences still hinder real-world deployment. However, the fusion of multimodal inputs (e.g., gesture + facial cues) and continuous learning models holds promise for overcoming these limitations.

Table 2: Literature Survey

Author(s) & Year	Title / Study Focus	Methodologies Used	Key Innovations / Findings	Relevance to Accessibility
Sharma et al. (2019) [16]	*Vision-based ISL Gesture Recognition using CNNs*	CNN, Open CV, Real-time gesture detection	Achieved 92% accuracy in real-time ISL alphabet recognition using deep learning	Enables real-time interaction for Deaf users via computer vision
Patel & Kumar (2021) [17]	*Hybrid Feature Extraction for Indian Sign Language*	LBP + GLCM + SVM Classifier	Improved texture-based feature extraction for static gestures	Enhances understanding of subtle hand shapes, crucial for mute communication
Singh et al. (2020) [18]	*Sign2Text: ISL Sentence-to-Text Translation*	RNN + Sequence Modeling	Converts gesture sequences into grammatically correct Hindi/English text	Bridges daily conversation gaps for Deaf individuals
Deshmukh & Iyer (2018) [19]	*Gesture to Speech for ISL Alphabets*	Arduino + Sensor Gloves	Built a wearable device to convert ISL gestures to audible speech	Empowers Deaf-Mute users to "speak" through gesture-to-voice systems
OpenAI (2023) [20]	*Multimodal Language Models for*	GPT-style vision-language models	Unified vision-text model learns	Paves the way for

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	Sign Recognition		Gestures with context awareness	multilingual and cross-modal ISLR
Chavan et al. (2022) [21]	*Augmented Reality for ISL Learning*	AR, 3D Hand Animation, Mobile App	Introduced interactivesign learning via AR based mobile interface	Makes ISL education accessible to hearing people, enhancing mutual learning
Bhable & Team (2025) [22]	*Helping Hands: ISL & Roman Alphabet Typeface*	Typeface Design, Semiotics, Cognitive Testing	Developed a dual-script font to support ISL learning via visual-symbol fusion	Improves early-stage ISL literacy and awareness in mainstream society

METHODOLOGY

- Our proposed model is built on a structured six-step pipeline designed to recognize Indian Sign Language gestures with precision and efficiency. The core stages include:
- Database Collection – Gathering a diverse set of gesture samples to ensure model robustness.
- Preprocessing – Enhancing image quality through filtering and contrast optimization.
- Feature Extraction – Employing advanced techniques such as Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) to capture distinctive gesture characteristics.
- Classification – Utilizing powerful algorithms like K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, Gaussian Naive Bayes, and Logistic Regression to categorize gestures accurately.
- Recognition – Matching the classified gestures to their corresponding ISL symbols.
- Text Generation – Converting recognized gestures into readable and meaningful text for seamless communication.

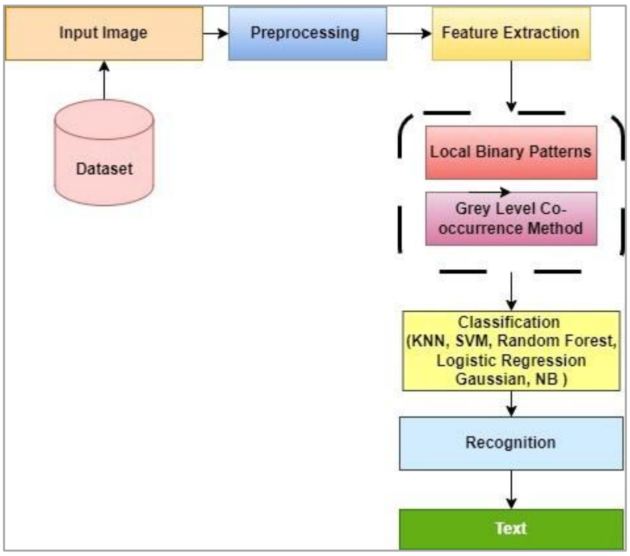

Fig 1: Design and Implementation Strategy

A. Database:

Fostering communication between Deaf and hearing communities is essential for building an inclusive society. One impactful approach involves presenting Indian Sign Language (ISL) graphically alongside Roman letters, enabling non-Deaf individuals to more easily learn and engage with this vital form of expression. This concept comes to life through the innovative “Helping Hands” typeface, which artfully merges familiar Roman alphabets with ISL gestures to promote faster recognition and understanding. Initiatives like “Helping Hands” not only improve accessibility in Deaf education but also emphasize the cultural and communicative importance of sign language in everyday public life.

B. Image Resizing and Segmentation in Preprocessing

To ensure uniformity and streamline computational demands, input images are resized to a consistent dimension. This standardization facilitates more efficient and accurate processing across the recognition pipeline. The resizing operation follows the proportional scaling formula:

Once resized, the next step is image segmentation—a critical phase where each image is partitioned into meaningful regions. In the context of sign language, this process isolates essential elements such as hand gestures, background, and other distinguishable features. This segmentation allows the system to focus only on relevant gesture data. To further refine this process, binary thresholding is applied. This technique converts grayscale images into binary format based on a predefined intensity threshold. It operates as follows:

This binary transformation simplifies the image by emphasizing the hand region (foreground) while suppressing irrelevant background noise, thereby enhancing gesture detection accuracy.

Fig 3: a) original b) Grayscale c) Segmented

C. Feature Extraction

Feature extraction plays a pivotal role in applications such as image matching and retrieval by transforming rich visual data into compact, informative feature vectors. This process involves isolating key

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distinguishing traits from segmented images to create a unique digital fingerprint for each gesture. Our approach leverages a fusion of powerful texture analysis techniques Gray-Level Co-occurrence Matrix (GLCM) **and** Local Binary Patterns (LBP) to generate robust and discriminative feature vectors that capture both spatial relationships and fine-grained textures within the image.

LBP (Local Binary Pattern):

The Local Binary Patterns (LBP) operator assigns a unique binary label to each pixel by comparing its intensity with that of its neighboring pixels. This pixel-wise encoding effectively captures textural features, including edges, corners, and local variations—making it highly suitable for image classification tasks.

To extract LBP features, the image is divided into small local regions, and histograms of the resulting binary patterns are computed for each region. These histograms are then concatenated to form the LBP feature vector, which serves as a powerful representation of the image's texture.

The standard LBP operates on a 3×3 pixel block, where the central pixel acts as a threshold. Each surrounding pixel is compared to the center:

- If a neighbor's intensity is greater than or equal to the center, it is assigned 1; otherwise, 0.
- This comparison yields an 8-bit binary code, which is then converted to a decimal value.

Mathematically, the LBP operator can be expressed as:
$LBPP,R(p)=\sum^{P-1} i=0 s(gi-gc)\times 2i$

where:

- $LBPP,R(p)LBPP,R(p)$ is the LBP value for pixel pp using PP sampling points on a circle of radius RR around the center pixel,
- $gcgc$ is the intensity of the center pixel,
- $gigi$ is the intensity of the ii-th sampling point on the circle,
- $(x)s(x)$ is the sign function.

GLCM:

In the realm of digital image processing, the Gray-Level Co-occurrence Matrix (GLCM) stands out as a powerful tool for texture analysis. It captures the spatial relationship between neighboring pixels by considering their relative positions—defined by distance and angle—and their gray-level intensities. By quantifying how often pairs of pixel values occur in a specified spatial configuration, GLCM uncovers underlying texture patterns within the image.

From this matrix, several key texture features can be extracted—contrast, homogeneity, correlation, and dissimilarity—each offering unique insights into the image's structural composition. These features are essential for tasks like texture classification, pattern recognition, and image segmentation, enabling machines to distinguish between different surfaces or gesture details in applications like sign language recognition.

Mathematically, the GLCM GGG is computed for a given displacement vector (dx,dy), where each element of the matrix counts how often a pixel with gray level gig_igi at location (x,y) is spatially related to a pixel with gray level gjg_jgj at (x+dx,y+dy)) in the image I. This formulation provides a robust statistical representation of texture through spatial gray-level dependencies

EXPERIMENTAL RESULTS AND ANALYSIS

The experimental findings emphasize the effectiveness of combining Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) with various machine learning classifiers for Indian Sign Language (ISL) gesture recognition. A comparative study of performance metrics across models demonstrates how different feature-model pairings impact accuracy, precision, recall, and F1-score.

a) Experimental Work 1: LBP-Based Gesture Recognition

Gaussian Naive Bayes (NB) Model

By integrating LBP feature extraction with the Gaussian Naive Bayes classifier, the model achieved an accuracy of 95.07% in recognizing ISL gestures. It recorded a precision of 95.47%, indicating its strong ability to correctly identify relevant gestures. With a recall of 95.07%, it successfully captured most of the relevant signs in the dataset. The F1 Score of 95.09% reflects a well-balanced performance.

K-Nearest Neighbors (KNN) Model

This model demonstrated exceptional performance, reaching an accuracy of 99.29%. The precision (99.30%) and recall (99.29%) scores reveal a near-perfect capability to detect and classify ISL gestures. An F1 Score of 99.28% confirms the model's robustness and balance.

Random Forest Model

Random Forest emerged as one of the top performers, attaining an accuracy of 99.45%. With a precision of 99.46%, recall of 99.45%, and F1 Score of 99.45%, the model consistently excelled in accurately and comprehensively identifying gesture patterns.

Logistic Regression Model

In contrast, the Logistic Regression model showed significant limitations, recording a low accuracy of just 7.50%. Its precision (5.26%), recall (7.50%), and F1 Score (2.99%) indicate poor predictive power and imbalance in performance.

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Support Vector Machine (SVM) Model

SVM performed poorly in this configuration, with an accuracy of only 4.81%. A precision of 0.26% and recall of 4.81% suggest near-total failure in detecting relevant gestures. The low F1 Score further confirms the inadequacy of SVM with LBP features in this context.

b) Experimental Work 2: GLCM-Based Gesture Recognition

Gaussian Naive Bayes (NB) Model

Using GLCM features, the Gaussian Naive Bayes classifier achieved 68.33% accuracy. The model maintained a precision of 65.19%, a recall of 68.33%, and an F1 Score of 65.33%, indicating moderate but balanced recognition capabilities.

K-Nearest Neighbors (KNN) Model

This model demonstrated strong results with GLCM, achieving an accuracy of 87.52%. The precision (87.69%), recall (87.52%), and F1 Score (87.43%) affirm its solid and reliable performance in recognizing gestures.

Random Forest Model

Random Forest once again showcased outstanding performance, attaining an accuracy of 95.64%. With a precision of 95.67%, recall of 95.64%, and F1 Score of 95.62%, it proves to be a consistent and effective model across different feature extraction methods.

Logistic Regression Model

Despite the use of GLCM features, Logistic Regression yielded only 48.12% accuracy. Both precision (48.00%) and recall (48.12%) suggest a modest capacity for gesture recognition. The F1 Score of 46.08% indicates a slightly unbalanced model performance.

Support Vector Machine (SVM) Model

SVM continued to underperform, achieving a low accuracy of 28.83%. With a precision of just 18.32%, a recall of 28.83%, and a poor F1 Score of 20.17%, it struggles to recognize and classify ISL gestures effectively when paired with GLCM features.

EXPERIMENTAL RESULT

To assess the effectiveness of our real-time Indian Sign Language (ISL) detection system, we employed key performance metrics such as accuracy and inference time. The system showcased impressive accuracy in recognizing ISL gestures from live video feeds, indicating its promise as a practical tool for accessible communication between Deaf and hearing individuals. While the results are encouraging, the system does face challenges particularly in adapting to variable lighting conditions and complex hand articulations. These limitations highlight the need for continued research and development to enhance the system's robustness, adaptability, and real-world applicability, especially in diverse environments where consistent performance is critical for user trust and adoption.

a. Shows **L** aliphatic sign

b. Shows **R** aliphatic sign

c. Shows **F** aliphatic sign

D. Shows **C** aliphatic sign

Fig. 5: shows some Indian sign language demonstrated using our real-time system.

We assessed the performance of our real-time Indian Sign Language (ISL) detection system using key metrics such as inference time and classification accuracy. The results revealed a high level of precision in recognizing ISL gestures from live video streams, highlighting the system's promise as an effective tool for accessible and inclusive communication. While the system performs impressively in controlled environments, it still faces challenges when adapting to variable lighting conditions and complex hand articulations. Nevertheless, its potential to empower individuals with hearing impairments is significant. Continued research and refinement are essential to enhance its robustness, environmental adaptability, and overall usability in real-world applications.

Table 2: Results using LBP Features

Algorithm	Accuracy	Precision	Recall	F1 Score
Gaussian NB	95.07%	95.47%	95.07%	95.09%
KNN	99.29%	99.30%	99.29%	99.28%
Random Forest	99.45%	99.46%	99.45%	99.45%
Logistic Regression	7.50%	5.26%	7.50%	2.99%

In Experiment 2, which utilized Gray-Level Co-occurrence Matrix (GLCM) features for recognizing Indian Sign Language gestures, the K-Nearest Neighbors (KNN) and Random Forest algorithms outperformed other classifiers. They delivered impressive accuracy scores of 87.52% and 95.64%, respectively—highlighting their strong ability to capture and interpret texture-based gesture patterns. Their high recall and F1 scores further validated the effectiveness of these models in robust gesture classification. Interestingly, Gaussian Naive Bayes (NB) also exhibited a reasonably balanced performance, achieving an accuracy of 68.33%, despite its assumption of feature independence. In contrast, Support Vector Machine (SVM) and Logistic Regression fell short, recording significantly lower accuracies of 28.83% and 48.12%, respectively. These results suggest that linear decision boundaries may not be well-suited for the complex, texture-driven feature space defined by GLCM in this context. In the task of recognizing Indian Sign Language gestures using GLCM-derived features, K-Nearest Neighbors (KNN) and Random Forest algorithms demonstrate superior overall performance, delivering high classification accuracy. Interestingly, Gaussian Naive Bayes also yields commendable results, proving to be a lightweight yet effective alternative. In contrast, Support Vector Machines (SVM) and Logistic Regression tend to underperform, offering comparatively lower accuracy in gesture classification.

Table 2: Results using GLCM Features

Algorithm	Accuracy	Precision	Recall	F1 Score
SVM	28.83%	18.32%	28.83%	20.17%
Logistic Regression	48.12%	48.00%	48.12%	46.08%
GaussianNB	68.33%	65.19%	68.33%	65.33%
KNN	87.52%	87.69%	87.52%	87.43%
Random Forest	95.64%	95.67%	95.64%	95.62%

CONCLUSION

The effectiveness of some classifiers over others is seen in our research paper's examination of the recognition of Indian sign language movements using Gray-Level Co-occurrence Matrix (GLCM) data. With high accuracy ratings of around 87.52% and 95.64%, respectively, the K-Nearest Neighbors (KNN) and Random Forest algorithms stand out as the best. Their impressive F1 scores, recall, and accuracy highlight how well they categorize motions using GLCM features. With a balanced classification performance and an accuracy of 68.33%, Gaussian Naive Bayes (NB) likewise exhibits commendable performance. However, the classification accuracies of Support Vector Machine (SVM) and Logistic Regression remain relatively low approximately 28.83% and 48.12%, respectively highlighting their limited effectiveness in this specific application. In contrast, our findings demonstrate that the K-Nearest Neighbors (KNN) and Random Forest algorithms yield significantly better performance when applied to GLCM-based features for recognizing Indian Sign Language gestures. These results point to promising avenues for real-world deployment of ISL recognition systems.

Nonetheless, to broaden the applicability of such models, further research and optimization are warranted particularly to improve the performance of classifiers like SVM and Logistic Regression within this domain.

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