

Metric-Learning Retrieval for Cross-Signer Isolated Sign Language Recognition

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Abstract

We address cross-signer Isolated Sign Language Recognition (ISLR) for Indian Sign Language as part of the WSLP-2026 shared task, where most target words have exactly one available training video and a system must recognize a query video performed by a signer never seen for that class during training. We approach this with a metric-learning encoder trained in two phases: pretraining on a large, multi-signer American Sign Language corpus to learn general signer-invariance, then fine-tuning on the target vocabulary using every real cross-signer recording we can responsibly source. Our preprocessing detects and extracts multiple performances of a word within a single recording as separate training samples, a technique not previously reported in SLR literature, and adapts a published missing-keypoint interpolation technique into a retrieval rather than classification pipeline. Our final system achieves 67.11% Top-1, 69.20% Top-5, and 70.34% Top-10 accuracy on the WSLP-2026 test-phase evaluation.

1 Introduction

Sign language recognition (SLR) is a key technology for reducing communication barriers for deaf and hard-of-hearing communities, yet the vast majority of SLR research and resources concentrate on a small number of well-resourced sign languages, chiefly American Sign Language (ASL), leaving languages such as Indian Sign Language (ISL) comparatively underserved despite large signing populations. Sign languages are also inherently multimodal, combining hand configuration, body posture, and motion dynamics, and highly variable across signers in speed, articulation, and style, making automatic recognition a challenging visual sequence modeling problem even where resources are plentiful.

In this paper, we address Isolated Sign Language Recognition (ISLR) for ISL as part of the WSLP-2026 shared task: given a query video, recognize which word from the task vocabulary it depicts.

Two central challenges characterize this setting:

- **Extreme per-class scarcity:** for the WSLP-2026 vocabulary, the large majority of target words have exactly one available training video, ruling out the many-examples-per-class training most SLR systems assume.
- **Cross-signer generalization:** a system must recognize a query video performed by a signer whose body proportions, signing speed, and style it has never observed for that class, distinct from the within-signer or seen-signer evaluation common in prior SLR work.

We address these challenges with a metric-learning encoder trained in two phases: pretraining on a large, multi-signer American Sign Language corpus to learn general signer-invariance, then fine-tuning on the target vocabulary using every real cross-signer recording we can responsibly source. Because most classes provide only one training example, we frame recognition as nearest-neighbor retrieval in a learned embedding space rather than closed-set classification (§3).

Our preprocessing pipeline detects and extracts multiple performances of a word within a single dictionary-style recording as separate training samples, a technique not previously reported in SLR literature to our knowledge (§3.2), and adapts a published missing-keypoint interpolation technique, validated only for classification on a different landmark layout, into our retrieval pipeline (§3.2).

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2 Related Work

Sign language datasets. Word-level SLR has been driven substantially by American Sign Language resources: Purdue RVL-SLLL ASL (Wilbur and Kak, 2006), WLASL (Li et al., 2020), and MS-ASL (Vaezi Joze and Koller, 2019), alongside language-specific corpora such as LSA64 for Argentinian Sign Language (Ronchetti et al., 2023) and DEVISIGN for Chinese Sign Language (Chai et al., 2014). For Indian Sign Language specifically, INCLUDE (Sridhar et al., 2020) and CISLR (Joshi et al., 2022) are available word-level resources.

Prior work on this shared task. WSLP’s inaugural edition (WSLP-AACL-2025) hosted a word-level recognition task of matching scale (4,398 videos), with reported per-class scarcity consistent with the task we address (Reddy and Kamakshi, 2025 report 80% of classes have at most 2 samples, median exactly 1). Reddy and Kamakshi (2025) establish a closed-set classification baseline: MediaPipe landmarks (Lugaresi et al., 2019) (75 points, no face) into a dilated-convolution temporal convolutional network, reporting 54% Top-1 / 78% Top-5 on their own 3,517/879 train/validation split. The different split and closed-set (rather than retrieval-based) formulation mean the numbers are not directly comparable.

Architectures. Early SLR work relied on CNNs (Tran et al., 2015) and, given sign language’s inherently temporal structure, LSTMs (Sams et al., 2023; Khartheesvar et al., 2023; Liao et al., 2019); graph neural networks (Yu et al., 2018) and inflated 3D convolutions (Carreira and Zisserman, 2017) model spatial skeleton structure and spatiotemporal video features respectively. Transformer architectures (Vaswani et al., 2017), despite their success elsewhere, remain comparatively under-explored in SLR, with some recent applications showing promising results (Camgoz et al., 2020; Boháček and Hruš, 2022). Our encoder follows this transformer lineage, adapting a per-landmark-group masked embedding concept (Hasan and Adnan, 2025): independently embedding each landmark group. Ensembling has also seen limited application in this space (Hruš et al., 2022): one approach uses majority voting across independently-trained models (Hasan and Adnan, 2025), which suits closed-set classification but

Source	Videos	Classes
WSLP task videos	4,398	4,356
CISLR <code>test.csv</code>	1,723	968
CISLR <code>prototype.csv</code>	2,018	2,017
Google ASL Signs (GISLR) ¹	94,477	250

Table 1: Training data sources in the final system.

does not transfer directly to the open-vocabulary retrieval setting we address; we discuss this design choice in §3.5.

Per-class scarcity and cross-signer generalization. The specific combination we address (as few as one training example per class, generalization required to an unseen signer) is comparatively rare as an explicit evaluation setting in prior SLR work, which more commonly evaluates within-signer or many-examples-per-class regimes. Our repetition-mining contribution (§3.2) is related to, but distinct from, sliding-window multi-crop sampling from long clips (which is blind to performance boundaries rather than aligned to them) and to sign-spotting / dictionary alignment work (Momeni et al., 2020), which aligns dictionary and continuous signing but does not, to our knowledge, convert detected intra-video repetitions into additional training supervision with an ablation demonstrating their value.

3 Method

We address cross-signer Isolated Sign Language Recognition (ISLR) for Indian Sign Language (ISL): given exactly one training example for most target words, a system must recognize a query video of that word performed by a signer never seen for that class during training. This setting differs from standard closed-set sign classification in that the model cannot rely on having observed diverse performers of every class; it must instead learn a general notion of signer-invariance and apply it zero-shot to unseen classes and signers at test time. Figure 1 gives an overview of the full pipeline.

3.1 Data Sources

Our training pool combines the shared task’s own data with three external cross-signer sources, summarized in Table 1.

The WSLP task’s own training data provides almost exclusively *one video per class*: the core difficulty of the task. CISLR (Joshi et al., 2022),

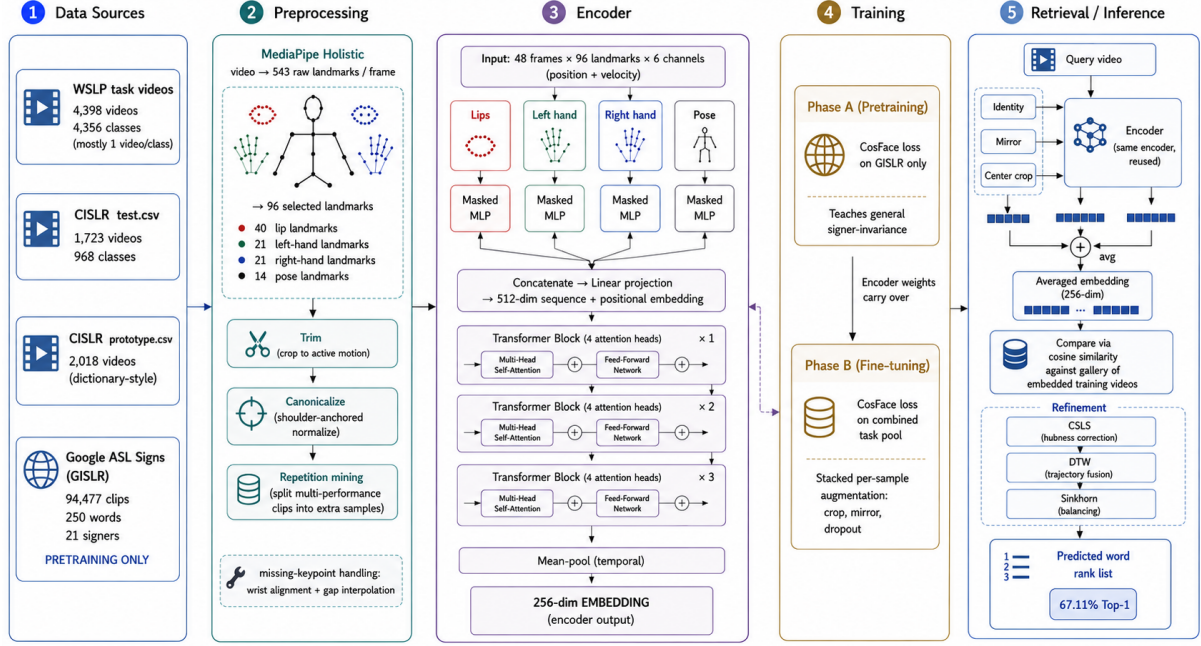


Figure 1: Overview of the pipeline: external cross-signer sources augment the task’s own data (§3.1); preprocessing and a per-group masked Transformer encoder (§3.2–§3.3) produce embeddings trained via two CosFace phases (§3.4); at inference, an averaged query embedding is compared against the training gallery and refined via CSLS, DTW, and Sinkhorn balancing (§3.5).

an Indian Sign Language corpus, supplies two components. `test.csv` contributes extra-signer recordings that happen to overlap the task vocabulary. `prototype.csv`, a large (4,765-video) dictionary-style set, is vocabulary-matched to contribute 2,018 videos, 1,049 of them for classes that otherwise had only a single training video (§5.2).

Google ASL Signs (GISLR) is the Kaggle competition training release of the PopSign ASL corpus (Starnier et al., 2023) (250 words, 21 signers, ~94,477 clips), used exclusively for pretraining (§3.4). Although it is a different sign language, it provides the one thing our task data structurally lacks: many distinct signers performing the same word, which is what makes learning general signer-invariance possible before ever seeing the target vocabulary.

3.2 Preprocessing

Each video is processed through MediaPipe Holistic (Lugaresi et al., 2019) to 543 raw landmarks per frame, from which we select 96 (40 lip, 21 left-hand, 21 right-hand, 14 pose including shoulders and wrists). Three preprocessing steps were retained after a component ablation (§5.1) that tested five candidate steps in isolation and removed-from-the-full-recipe:

- **Trim**: crop each clip to its active motion span via a motion-energy detector, removing idle padding before and after the sign.
- **Canonicalize**: shoulder-anchored translation and scale normalization, removing camera-distance and body-size variation across recordings.
- **Repetition mining**: some dictionary-style source videos contain the signer performing the target word more than once. We detect repeated bursts via the same motion-energy signal and extract each as an additional training sample, effectively mining extra supervision from a single recording.

A preprocessing-time mirroring step and a DTW-based consistency filter on mined repetitions were both tested and dropped; both were harmful in isolation and their removal measurably improved the full recipe (§5.1).

Missing-keypoint handling. MediaPipe frequently fails to detect a hand for several consecutive frames, and its independently-estimated pose-model wrist and hand-model wrist positions do not always agree. We adopt a published interpolation and alignment technique (Hasan and

Adnan, 2025): (i) whenever a hand is detected, the pose model’s wrist estimate and three adjacent landmarks (the pinky, index, and middle finger bases) are each replaced by the hand model’s own corresponding position (their homogeneous-matrix formulation, algebraically equivalent to direct assignment); (ii) for an interior span of frames where a hand is missing but bounded by valid frames on both sides, each of the 21 hand landmarks is linearly interpolated between the two boundary frames. We re-implemented this technique against our own 96-landmark layout and independently verified it against real data before integration (correct target column indices, exact reproduction of the published interpolation formula, and a real test case with 38 missing frames reduced to 1 unrecoverable frame (a leading/trailing gap with no valid frame on one side, which the technique does not cover by design).

3.3 Encoder Architecture

The encoder embeds each 48-frame, 96-landmark, 6-channel (position + masked velocity) clip into a 256-dimensional representation. Each of four landmark groups (lips, left hand, right hand, pose) is independently embedded by a masked two-layer MLP: if a group is entirely absent in a frame, its output is zeroed rather than passed through the network, preserving an explicit missingness signal rather than treating a zero-filled input as informative. A published alternative (Hasan and Adnan, 2025) instead learns a trainable embedding for missing groups; our four group embeddings are also combined by concatenation and linear projection to a 512-dimensional sequence, rather than their learned weighted sum. The sequence is added to a learned positional embedding and passed through 3 Transformer blocks (4 attention heads, MLP ratio 2, dropout 0.1) using standard scaled dot-product multi-head attention (Vaswani et al., 2017). The sequence is mean-pooled and projected to the final 256-dimensional embedding. No classification head is attached to the encoder; training and inference both operate purely in embedding space via the metric-learning objective described next.

3.4 Training

Training proceeds in two phases.

Phase A (pretraining). We pretrain with a CosFace (Wang et al., 2018) metric-learning objec-

tive on GISLR (§3.1), which pushes different signers’ performances of the same word toward the same region of embedding space. Two of GISLR’s 21 signers are held out entirely, giving a genuine cross-signer retrieval check during development. 30 epochs, batch size 1,024, learning rate 1×10^{-4} , CosFace scale 30 / margin 0.20.

Phase B (fine-tuning). The encoder is then fine-tuned with the same CosFace objective on the task’s own combined training pool (§3.1–3.2), up to 15 stages of 4 epochs each, batch size 512, learning rate 1×10^{-4} , CosFace scale 30 / margin 0.30. Each training sample additionally receives per-sample augmentation: random temporal crop (0.70–1.0 of clip length), mirror (25% probability), and frame dropout (8%), stacked; a fourth candidate, affine jitter, is disabled in the best configuration.

3.5 Retrieval

At inference, each query is embedded with test-time augmentation (identity, mirror, and a center temporal crop, averaged). Similarity to the training gallery is computed by cosine distance, aggregated per class by taking the maximum similarity over that class’s gallery samples, then refined by CSLS hubness correction (Conneau et al., 2018) ($k=10$), a dynamic-time-warping trajectory-fusion signal on wrist trajectories (weight 0.3), and Sinkhorn transductive balancing (Cuturi, 2013). Isolated testing of Sinkhorn earlier in development found it harmful; in the final configuration, combined with CSLS and DTW fusion, it is genuinely part of the best result; we report this as an interaction effect rather than a reversal (§5).

4 Experiments

We evaluate on the WSLP-2026 shared task’s own splits: 4,398 training videos (4,356 unique classes), a 109-video validation set (scored during a training phase), and a 526-video test set (scored during the subsequent, final test phase; this is the result reported throughout §5). The organizers’ evaluation reports Top-1, Top-5, and Top-10 retrieval accuracy.

5 Results

Our final system achieves **67.11% Top-1**, 69.20% Top-5, and 70.34% Top-10 on the WSLP-2026 test-phase evaluation.

Configuration	Top-1
Canonicalize + Trim + Rep. mining + Mirror + DTW filter	50.46
Canonicalize + Trim + Rep. mining + DTW filter	52.29 (+1.83)
Canonicalize + Trim + Rep. mining	53.21 (+0.92)
Canonicalize + Rep. mining	52.29 (−0.92)

Table 2: Sequential removal of Mirror and the DTW consistency filter from the full preprocessing recipe, then Trim as a confirmation check (validation-phase scores). Canonicalize + Trim + Rep. mining (row 3) is the winning configuration.

5.1 Component Ablation

We tested five candidate preprocessing steps (§3.2) on an earlier checkpoint of the system (53.21% Top-1 baseline era; relative effects are what matter here, not the absolute score, which the later data additions in §5.2 substantially improved). Canonicalize and repetition mining were each confirmed positive in isolation (canonicalization accounts for the large majority of the full pipeline’s value; repetition mining alone adds +1.84 points) and are held constant throughout Table 2, which traces the sequential removal of the remaining three candidates from the full recipe.

Two results are worth highlighting because the double confirmation (isolated *and* removed-from-recipe) rules out a spurious correlation: trim helps alone (+0.92) and removing it from the winning recipe hurts (the final row above), confirming it is genuinely load-bearing rather than redundant with something else in the recipe. Mirror-time augmentation (−2.75 alone) and the DTW consistency filter (−0.92 alone) both hurt in isolation *and* their removal is exactly what produces the two gains shown above: a consistent, not merely isolated, negative signal.

5.2 Cross-Signer Data Source Ablation

Table 3 shows the effect of adding the CISLR `prototype.csv` dictionary set (§3.1) to the training pool.

Adding the prototype set alone produces a +15.60 point improvement, larger than every subsequently tested component or hyperparameter change combined (§5.1). We verify this is not a leakage artifact: prototype clips are short, single-burst dictionary performances, structurally distinct from the task’s own longer, multi-burst recordings (confirmed via an independent motion-energy duration measurement), and a content-level duplicate

Configuration	Top-1
Baseline (task + CISLR <code>test.csv</code>)	53.21
+ CISLR prototype extras	68.81 (+15.60)
+ longer training, no affine jitter	71.56* (+2.75)

Table 3: Cumulative effect of adding CISLR prototype extras (§3.1), validation-phase scores. *Two simultaneous changes (Phase B stage count and disabling one augmentation operation); the combined effect is confirmed, the individual attribution between the two is not.

check (frame-hash comparison across all splits) found zero duplicates.

6 Conclusion

We presented a metric-learning retrieval system for cross-signer Isolated Sign Language Recognition on Indian Sign Language, addressing the WSLP-2026 shared task. A two-phase encoder, pretrained on a multi-signer American Sign Language corpus and fine-tuned on the target vocabulary combined with real cross-signer recordings, achieves 67.11% Top-1, 69.20% Top-5, and 70.34% Top-10 accuracy on the test-phase evaluation. Beyond the final system, we contribute a repetition-mining technique for extracting additional training supervision from dictionary-style recordings, and a cross-paradigm port of a published missing-keypoint interpolation technique into a retrieval setting. Future work could explore further sources of real cross-signer supervision, which this work finds to be the central lever for generalizing to unseen signers under extreme per-class scarcity.

7 Limitations

Several components are not isolated with dedicated ablations on the final configuration. We do not report the final system trained with and without Phase A (ASL) pretraining, nor a breakdown of the retrieval refinement stack (CSLS, DTW fusion, Sinkhorn balancing) into its individual and combined contributions; Section 3.5 reports Sinkhorn’s isolated-versus-combined interaction effect as observed during development, not as a controlled ablation on the released system. The missing-keypoint interpolation fix (Section 3.2) is part of the final recipe, but its contribution is confounded with a simultaneous retuning of training hyperparameters, so its standalone effect cannot be separated post hoc.

The preprocessing ablations in Table 2 are measured on a 109-video validation set, where a 0.92-point difference corresponds to a single additional correct prediction, and we do not report results across repeated random seeds. Separately, nominally similar retrained variants of this pipeline showed roughly a 2-point spread in test-phase Top-1 across submissions, so deltas of this size should be read with that variance in mind rather than as precise, seed-independent effects.

We verify that CISLR extras contain no exact content duplicates with the task’s own splits (Section 5), but signer identities are not available for either corpus, so we cannot verify that no signer appears in both CISLR extras and the WSLP validation or test splits. Cross-signer generalization results should be read with this caveat.

This paper’s contribution is the retrieval formulation, data sources, and preprocessing findings for this task, not an architecture search: we do not compare against modern video-language foundation models or alternative spatiotemporal backbones, and Top-5/Top-10 gains over Top-1 are reported without a retrieval-rank error analysis.

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