# BANZ-FS: BANZSL FINGERSPELLING DATASET

# **Anonymous authors**

000

001 002 003

004

021

024

025

026

027

028

029

031

034

038

039

040

041

042

043

044

045

046

048

Paper under double-blind review



Figure 1: **Overview of BANZ-FS dataset sources and coverage.** The figure shows fingerspelling instances for all 26 letters (A–Z) and 10 digits (0–9) from three sources: ABC News, Lab Recordings, and Web Videos. News instances reflect formal, live interpretations by professional signers. Lab recordings offer clean, controlled settings ideal for analysis. Web videos capture diverse, in-the-wild signing styles across various environments.

#### ABSTRACT

Fingerspelling plays a vital role in sign languages, particularly for conveying names, technical terms, and words not found in the standard lexicon. However, evaluation of two-handed fingerspelling detection and recognition is rarely addressed in existing sign language datasets—particularly for BANZSL (British, Australian, and New Zealand Sign Language), which share a common two-handed manual alphabet. To bridge this gap, we curate a large-scale dataset, dubbed BANZ-FS, focused on BANZSL fingerspelling in both controlled and real-world environments. Our dataset is compiled from three distinct sources: (1) live sign language interpretation in news broadcasts, (2) controlled laboratory recordings, and (3) diary vlogs from online platforms and social media. This composition enables BANZ-FS to capture variations in signing tempos and fluency across diverse signers and contents. Each instance in BANZ-FS is carefully annotated with multi-level alignment: video  $\leftrightarrow$  subtitles, video  $\leftrightarrow$  fingerspelled letters, and video  $\leftrightarrow$  target lexicons. In total, BANZ-FS includes over 35,000 video-aligned fingerspelling instances. Importantly, BANZ-FS highlights the unique linguistic and visual challenges posed by twohanded fingerspelling, including handshape coarticulation, self-occlusion, intraletter variation, and rapid inter-letter transitions. We benchmark state-of-the-art models on the key tasks, including fingerspelling detection, isolated fingerspelling recognition, and fingerspelling recognition in context. Experimental results show that BANZ-FS presents substantial challenges while offering rich opportunities for BANZSL understanding and broader sign language technology. The dataset and benchmarks are available at BANZ-FS.



Figure 2: Overview of typical fingerspelling phenomena and visual challenges captured by the BANZ-FS dataset. The pie chart (top-left) illustrates the proportion of different fingerspelling phenomena annotated within the dataset. Representative examples below highlight diverse real-world cases, such as exact matches ("equity"), lexical abbreviations ("equipment"  $\rightarrow$  "EQ"), spelling errors ("Maguire" misspelled as "Maquire"), acronym use ("Greater Western Sydney"  $\rightarrow$  "GWS"), and inline corrections ("miimiles" corrected to "miles"). The bottom row (green boxes) highlights key visual challenges specific to two-handed fingerspelling systems, such as self-occlusion, intraletter variation, and rapid inter-letter transitions, further underscoring the complexity of accurate fingerspelling recognition and translation in BANZSL.

# 1 Introduction

Sign languages (SL) are natural languages that serve as primary modes of communication for Deaf and hard-of-hearing individuals, enabling rich self-expression and full participation in society. Like spoken languages, sign languages possess their own grammars and lexicons, and they vary widely across regions—even in places that share a common spoken language. For example, American Sign Language (ASL) (Duarte et al., 2021; Shi et al., 2022; Uthus et al., 2023; Tanzer & Zhang, 2024; Li et al., 2020a) and Australian Sign Language (Auslan) (Shen et al., 2023; 2024; Sheng et al., 2024) are linguistically distinct, each with unique phonological, lexical, and syntactic features. To bridge communication between Deaf and hearing communities, sign language translation (SLT) (Shen et al., 2025) systems have been developed to automatically translate sign videos into spoken languages.

Among sign languages, fingerspelling (FS), the manual representation of alphabets and numbers, plays a critical role in SLT (Shen et al., 2023; Tanzer, 2024b; Georg et al., 2024; Kim et al., 2017; Papadimitriou et al., 2024), particularly for expressing proper nouns, technical terms, and items not represented in the standard sign lexicon. Unlike single-handed systems, such as ASL (Shi et al., 2021; Padden., 1998; Tanzer, 2024a), BANZSL¹ employs a distinctive two-handed fingerspelling system. This two-handed system introduces significant challenges for machine translation (see the bottom

<sup>&</sup>lt;sup>1</sup>**G** BANZSL refers to a sign language family which encompasses BSL, Auslan and NZSL. These sign languages can be considered as dialects of BANZSL due to their shared manual alphabet, grammatical structure, and substantial lexical overlap.

row of Figure 2), such as frequent self-occlusion, high intra-letter variations, and rapid handshape transitions. Hence, accurate recognition of fingerspelling is crucial, as it frequently conveys essential semantic content, such as named entities, numerical data, and domain-specific vocabulary that lack conventional sign equivalents.

Despite significant progress in sign language research (Huang et al., 2018; Zhou et al., 2021; Shi et al., 2022; Duarte et al., 2021; Camgöz et al., 2018; Uthus et al., 2023; Tanzer & Zhang, 2024; Shen et al., 2023; 2024), most publicly available datasets focus on single-handed fingerspelling understanding task, such as those used in ASL (Shi et al., 2021; Padden., 1998; Tanzer, 2024a; Georg et al., 2024) and GSL (Papadimitriou et al., 2024), leaving the two-handed fingerspelling system of BANZSL (Shen et al., 2024; Prajwal et al., 2022) comparatively underexplored. Moreover, existing datasets often lack the scale and linguistic realism required for fingerspelling research. In particular, they rarely capture naturally occurring phenomena, such as spelling errors, lexical abbreviations, acronyms, and inline corrections, which are commonly encountered in practical scenarios. This highlights a critical gap: the need for a large-scale, real-world BANZSL fingerspelling dataset to facilitate the study on BSL, Auslan and NZSL.

To address this gap, we introduce **BANZ-FS**, a large-scale dataset dedicated to BANZSL finger-spelling, collected from both real-world and controlled environments. As shown in Figure 1, BANZ-FS integrates multiple sources to reflect diverse and authentic usage scenarios: (1) professional live Auslan interpretations from *ABC News with Auslan* broadcasts (capturing formal, high-register discourse); (2) controlled laboratory recordings (offering clean, high-quality reference data); and (3) user-generated vlog content from online platforms and social media (representing casual, daily communication). This diverse composition allows BANZ-FS to capture a broad spectrum of signing tempos and registers, from formal broadcast interpretation to everyday interaction.

Specifically, BANZ-FS comprises more than 35,000 aligned fingerspelling instances. During annotating fingerspelling, we additionally align 40 hours of Auslan news footage, which not only substantially extends the prior benchmark Auslan-Daily News (Shen et al., 2023) but also allows us to investigate recognition accuracy of fingerspelling within contexts. Our annotation protocol includes fine-grained alignment across video  $\leftrightarrow$  subtitles, video  $\leftrightarrow$  fingerspelled letters, and video  $\leftrightarrow$  target lexicons. As illustrated in Figure 2, we explicitly annotate and categorize key linguistic phenomena prevalent in fingerspelling, including abbreviations, acronyms, misspellings, and inline corrections. Furthermore, our proposed dataset captures the visual and articulatory complexities inherent in two-handed fingerspelling systems, underscoring the challenges of accurate fingerspelling recognition in BANZSL.

With BANZ-FS, we investigate a range of fingerspelling-related tasks, including fingerspelling detection, isolated fingerspelling recognition and fingerspelling recognition in context. We benchmark publicly available state-of-the-art models on each task and then report the performance using corresponding evaluation metrics. Experimental results demonstrate that the complexity and realism of BANZ-FS pose significantly challenge to existing methods, highlighting its potential to drive progress in two-handed fingerspelling understanding. Overall, the contributions of this work are threefold:

- We curate the first large-scale fingerspelling dataset specifically for the BANZSL system, capturing real-world complexities across diverse contexts.
- We provide comprehensive multi-level annotations to support fingerspelling-related tasks, including fingerspelling detection, isolated fingerspelling recognition, and fingerspelling recognition within continuous sign language sentences.
- We benchmark state-of-the-art methods to highlight the unique challenges posed by BANZ-FS, and establish an ideal platform to evaluate fingerspelling recognition capabilities.

# 2 RELATED WORK

### 2.1 FINGERSPELLING DATASETS

Early research in sign language recognition primarily addressed isolated sign language recognition (Shen et al., 2024; Li et al., 2020a; Desai et al., 2023; Starner et al., 2023), but recent trends have progressively emphasized continuous sign language recognition recognition (Chen et al., 2022c; Min et al., 2021) and fingerspelling recognition (Shen et al., 2023; Kim et al., 2017; Shi et al., 2018;

Table 1: Comparison of the proposed **BANZ-FS** dataset with existing datasets widely used for fingerspelling-related tasks. "FSR-Context", "FSD", and "IFSR" represent Fingerspelling Recognition in Context, Fingerspelling Detection and Isolated Fingerspelling Recognition, respectively.

Dataset	SL	Video	Vocab.	# FS Seqs	#Signer	Source	FSR-Context	FSD	IFSR
Fleurs-ASL-FS (Tanzer, 2024a;b)	ASL	1.7K	-	0	5	Lab	✓		
SL-ReDu-Fing. (Papadimitriou et al., 2024)	GSL	1.5K	24	1.5K	21	Lab			✓
BOBSL-FS (Prajwal et al., 2022)	BSL	5K	26	5K	-	Web			✓
ChicagoFSVid (Kim et al., 2017)	ASL	4K	26	4K	4	Lab			✓
FSboard (Georg et al., 2024)	ASL	151K	36	151K	147	Smartphone			✓
ChicagoFSWild (Shi et al., 2018)	ASL	7K	26	7K	160	Web		✓	✓
ChicagoFSWild+ (Shi et al., 2019)	ASL	55K	26	55K	260	Web		✓	✓
Auslan-Daily Comm. (Shen et al., 2023)	Auslan	14K	3K	1K	49	TV&Web	✓	<b>√</b>	<b>√</b>
Auslan-Daily News (Shen et al., 2023)	Auslan	11K	13K	1K	18	TV&Web	✓	✓	✓
BANZ-FS (Ours)	BANZSL	35K	36	35K	116	Lab&Web	✓	✓	/

2019; Fayyazsanavi et al., 2024). Despite growing interest, as shown in Table 1, existing finger-spelling datasets largely concentrate on American Sign Language (ASL) and single-handed signing systems (Papadimitriou et al., 2024), such as ChicagoFSWild+ (Shi et al., 2019), ChicagoFSWild (Shi et al., 2018), FSBoard (Georg et al., 2024) and Fleurs-ASL-FS (Tanzer, 2024a;b). Among these, FSBoard (Georg et al., 2024) is currently the largest dataset, containing approximately 151K finger-spelling sequences collected from 147 signers, captured uniquely via smartphone in a single-handed manner. However, FSBoard is limited to recognition tasks due to the absence of segment-level annotations, which restricts its application in fingerspelling detection. Datasets capturing finger-spelling "in-the-wild", such as ChicagoFSWild (Shi et al., 2018) and ChicagoFSWild+ (Shi et al., 2019), have improved realism by sourcing content from online platforms, encompassing diverse signer appearances and environmental variations. It is worth noting that Fleurs-ASL-FS (Tanzer, 2024a;b) only provides sentence-level annotations indicating the presence of fingerspelling, without corresponding temporal boundaries. As a result, it can only be used for fingerspelling in context task, but not for fingerspelling detection or localization.

Regarding BANZSL-related resources, prior datasets such as Auslan-Daily (Shen et al., 2023) and BOBSL-FS (Prajwal et al., 2022) contain only a limited number of fingerspelling instances, and consequently provide insufficient support for developing and evaluating fingerspelling-specific tasks. Our proposed **BANZ-FS** dataset addresses these limitations by introducing over 35K aligned fingerspelling instances with comprehensive annotations suitable for fingerspelling detection and recognition tasks. In parallel with the annotation of BANZ-FS, we also engaged Auslan experts to extend the Auslan-Daily (Shen et al., 2023) News subset through additional annotation and alignment, resulting in a threefold increase in scale.

#### 2.2 FINGERSPELLING DETECTION AND RECOGNITION METHODS

Early fingerspelling detection (Shi et al., 2021) methods utilized visual features such as optical flow or predefined hand keypoints (Yang & Lee, 2010; Yanovich et al., 2016). However, such methods have primarily been evaluated in controlled environments, with limited effectiveness in unconstrained, real-world settings due to unreliable pose estimations (Tsechpenakis et al., 2006b;a). Recent approaches have favored recurrent neural networks (RNNs) (Luong et al., 2015) and transformer-based (Vaswani et al., 2017) architectures to enhance temporal modeling capabilities and robustness (Li et al., 2020c; Moryossef et al., 2020; Zuo et al., 2023; Pugeault & Bowden, 2011; Li et al., 2020a).

For fingerspelling recognition, convolutional neural networks (CNNs) combined with RNNs or Long Short-Term Memory (LSTM) networks have been widely employed (Schuster & Paliwal, 1997; Shi et al., 2021). Transformer-based models have recently emerged as powerful alternatives, effectively capturing long-range temporal dependencies and contextual information crucial for recognizing fingerspelled sequences (Boháček & Hrúz, 2022; Hu et al., 2024; Prajwal et al., 2022). Several studies have explored multimodal fusion approaches, integrating RGB frames, optical flow, and pose estimation features to enhance recognition accuracy (Jiang et al., 2021a;b; Zuo et al., 2023). While significant progress has been made, challenges remain, particularly regarding ambiguity due to similar handshapes across distinct letters and digits. Methods like those proposed in (Li et al., 2023; Fayyazsanavi et al., 2024) modify Transformer encoder-decoder architectures explicitly to mitigate ambiguities arising from visually similar fingerspelling representations.

# 3 BANZ-FS DATASET

In this section, we describe data collection for web-based fingerspelling data, as well as the recording protocol for the lab-collected instances<sup>2</sup>. We provide detailed statistics of the **BANZ-FS** dataset.

### 3.1 COLLECTION, CLEANING AND LABELLING PROCEDURE FOR WEB DATA

Collection. "ABC News with Auslan" and YouTube sources are open sources. Beginning in 2022, "ABC News with Auslan" has provided weekly broadcasts covering key domestic and international news events, as well as weather forecasts. It is an ongoing program, and previous work (Shen et al., 2023) aligned 45 videos collected up to May 2023, along with a small number of fingerspelling annotations. In this work, we extend the collection by acquiring an additional 80 videos spanning from May 2023 to April 2025. These broadcasts feature live sign language translation (simultaneous interpretation) by Auslan experts, intended for deaf and hearing-impaired viewers. News content inherently includes a rich set of fingerspelling scenarios, such as personal names, place names, organization names, phone numbers, and other proper nouns, making it an ideal source for studying fingerspelling phenomena. To further diversify our dataset, we also include several high-quality publicly available documentaries and educational videos interpreted with BSL and NZSL, primarily sourced from YouTube. These videos typically feature daily conversations, learning activities, or introductions to specific topics.

**Cleaning.** All original videos are accompanied by standard English dubbing and subtitles. We retrieve subtitles for each complete video, formatted as "[Start Time] subtitle [End Time]", with timing aligned to the spoken dubbing. Following the subtitle cleaning strategy proposed in Auslan-Daily (Shen et al., 2023), we perform simple cleaning operations: merge fragments ending in commas with their subsequent lines, split overlapping subtitles into separate sentences, and discard entries with only non-semantic fillers. As a result, we obtain approximately 30K complete and cleaned subtitles requiring further alignment with fingerspelling segments.

**Labelling.** To annotate fingerspelling instances, we invited experienced Auslan experts to assist in the labelling process. In particular, for news videos, we additionally perform temporal alignment to ensure segment-level consistency. For each video, we first employ AlphaPose (Fang et al., 2022; 2017; Li et al., 2019) to track all individuals in the scene. The annotation process proceeds in several steps: (1) verify and refine video-subtitle alignment; (2) identify the signer ID based on pose trajectories; (3) if fingerspelling is present, annotate the corresponding temporal segment; and (4) retrieve the associated target lexicon from the subtitle, if it exists. To guarantee the annotation quality of our dataset, we conduct a cross-check verification process during each data labelling procedure stage. Specifically, we ask each Auslan annotator as an examiner to cross-check around 5% of annotated video clips provided by another annotator. The video clips are chosen randomly. If the examiner finds more than 10% of annotated videos have obvious errors, a third annotator is invited to review and correct the annotations. Through the collaborative efforts of five Auslan experts and five annotators, we complete all annotations with approximately 500 work hours. Overall, our dataset contains the following **annotations**: (1) temporal boundaries of sign video clips; (2) temporal boundaries of fingerspellings; (3) lexical forms of fingerspellings; and (4) English transcriptions. These annotations can be further investigated for fingerspelling-related tasks.

# 3.2 COLLECTION FOR LAB DATA

To complement our web data, followed by (Shen et al., 2024), we record lab-controlled videos using a multi-camera RGB-D setup. The recording studio is equipped with a green screen and includes three Kinect-V2 cameras positioned at left-front, front, and right-front angles, along with a centrally placed RealSense camera. We invite participants with diverse Auslan experience, including deaf individuals, Auslan experts, and sign language learners. Participants are instructed to perform frequently used fingerspelling words and expressions commonly encountered in daily communication contexts. Each sign instance is verified by at least one expert to ensure expression accuracy, while the inclusion of volunteers enhances signer diversity and realism. This setup facilitates the study of cross-camera robustness and supports high-quality benchmarking under controlled conditions.

<sup>&</sup>lt;sup>2</sup>The original Auslan News data is provided by Auslan-Daily (Shen et al., 2023). Both the web-based and lab-collected portions of our dataset will be released under the **Creative Commons BY-NC-SA 4.0** license ©.

271

272

273274275276277278279280281282

284

287

289

291292293

295296

297

298

299

300

302

303

304

305

306

307

308

310

311

312

313

314

315

316

317318

319 320

321

322

323

Table 2: Key statistics of the BANZ-FS dataset across three data sources: ABC News with Auslan, Lab Capture, and YouTube. OOFS (out-of-training FS strings) are FS sequences that never appear in the training set, while FS Singletons occur only once in training.

	ABC No	ews with A	uslan		Lab Captur	re		YouTube		
Source Language Domain/Topic Video Resolution@FPS	128	Auslan News 30×720@2:	5	1920×10	- Daily Used 080@30/1280			SL&NZSI mmunicati Various		
Split	Train	Dev	Test	Train	Dev	Test	Train	Dev	Test	Total
Video Segments Signers Avg. FS Segments Tot. FS Chars Avg. FS Speed (chars/sencond) Tot. OOFSs FS Singletons	18,694 24 2.4 144,090 4.59 - 1,201	1,608 22 2.0 12,383 4.89 304	1,896 19 2.5 15,717 4.17 450	6,828 65 1.0 11,748 1.30	1,952 52 1.0 3,360 1.31 0	1,952 50 1.0 3,360 1.30 0	1,498 18 2.3 12,034 1.99	300 10 1.8 2,154 1.45 43	300 7 2.0 2,446 1.68 64	35,028 116 1.95 207,29 3.41 813 1,191
28.8000+ 150.7000 150.60000 150.60000 150.6000 1	5 6	Individu 6+	Auslan Expert  6. 9.1%  13.6%	9.1% 24.2!  Gender Male Female 37.9%	(b) Volunt	II 2000	( <sup>10</sup> 06.5)	tion of FS d	(2,2,3)	(c)
1 2 3 4 Number of FS segments	per detection						Time dura	tion of FS d	letection cli	p (second:
Number of FS segments	s per detection						Time dura	tion of FS d	etection cli	p (second
Number of FS segments	s per detection						Time dura	tion of FS d	letection cli	p (second
1 2 3 4 Number of FS segments	per detection						Time dura	tion of FS d	letection cli	p (second

Figure 3: (a) Distribution of the number of fingerspelling (FS) segments per clip. (b) Distribution of FS clip durations. (c) Distribution of signer demographics categorized by Auslan proficiency and gender. (d) Character frequency distribution across all FS clips.

#### 3.3 DATA STATISTICS

As shown in Table 2, we present key statistics of BANZ-FS to highlight the diversity and complexity of the dataset. BANZ-FS consists of over 35,000 annotated video segments sourced from news broadcasts, lab recordings, and online videos, covering 116 unique signers. The dataset is split into training, development, and test sets to facilitate fair evaluation of fingerspelling-related tasks. We segment each video by applying a 10-second sliding window around any detected FS segment. As a result, each detection clip may contain multiple FS instances. As shown in Figure 3, most clips contain only 1–2 FS segments and last less than 1.5 seconds, indicating that FS is often embedded briefly within continuous signing. Furthermore, the signer population includes a balanced mix of Auslan experts, deaf individuals, and volunteers, offering a wide range of signing styles and linguistic competence. The FS character distribution reveals a long-tail pattern: common letters such as A, E, and N appear frequently, while rare characters (e.g., numerals and less frequent letters) occur sparsely. This imbalance poses additional challenges for generalization and open-vocabulary recognition, especially in low-resource conditions. In addition, we report the number of out-of-training FS strings (OOFS) and FS singletons in Table 2, which quantify the presence of unseen or rare FS sequences and further reflect the open-set nature of the task. Further statistics can be found in Appendix Section B, Section C.5 and Section C.6.

# 4 OVERVIEW OF BANZ-FS TASKS AND EVALUATION METRICS

In this section, we provide an overview of the **BANZ-FS** benchmark tasks and their corresponding evaluation metrics, as illustrated in Figure 4.

**Isolated Fingerspelling Recognition (IFSR)** (Shi et al., 2018; 2019): Given a segmented fingerspelling clip  $\mathbb{V}_{fs} = \{I_{fs}, ..., I_{fe}\}$ , the goal of IFSR is to transcribe it into the corresponding

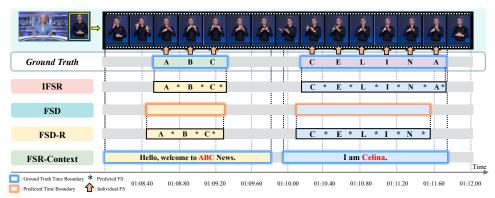


Figure 4: Overview of fingerspelling-related tasks in our BANZ-FS dataset.

letter sequence  $\hat{L} = \{l_1, ..., l_n\}$ . Evaluation Metric for IFSR is **Letter Accuracy** - Defined as  $1 - \frac{\text{EditDistance}(L^*, \hat{L})}{|L^*|}$ , where  $L^*$  is the ground-truth letter sequence and  $\hat{L}$  is the predicted sequence. This edit-distance-based metric captures the correctness of the full predicted sequence, accounting for insertions, deletions, and substitutions.

Fingerspelling Detection (FSD) (Shi et al., 2021): Given an untrimmed sign language video  $\mathbb{V} = \{I_1, I_2, \dots, I_T\}$  with T frames, the goal of FSD is to identify temporal segments  $(f_s, f_e)$  that localize fingerspelling intervals within  $\mathbb{V}$ . Each predicted segment corresponds to a time span where fingerspelling occurs. Evaluation Metrics for FSD is  $\mathbf{AP@IoU}$  - Average Precision calculated based on temporal Intersection-over-Union (IoU) between predicted and ground-truth segments. Higher IoU thresholds reflect stricter localization accuracy.

Fingerspelling Detection followed by Recognition(FSD-R) (Shi et al., 2021): This is a two-stage approach where a FSD model first predicts temporal segments from an untrimmed sign language video  $\mathbb V$ , and each predicted segment is subsequently processed by a fingerspelling recognizer to generate the corresponding letter sequence. Evaluation Metrics for FSD-R is AP@Acc - Average Precision computed using the accuracy of a downstream recognizer applied to each predicted segment.

Fingerspelling Recognition in Context (FSR-Context) (Tanzer, 2024b): Given a full sentence-level sign language video  $\mathbb V$  and its predicted spoken language translation  $\hat T$ , the task of FSR-Context is to evaluate how accurately the model transcribes fingerspelled terms embedded within the sentence. Specifically, fingerspelled spans annotated in the video are aligned with corresponding spans in the predicted translation, and character-level accuracy is measured. Evaluation Metrics for FSR-Context is Letter Accuracy.

# 5 BANZ-FS BENCHMARK

### 5.1 VIDEO REPRESENTATION

**Pose-based video feature representation:** Pose-based representations are robust against background clutters, lighting conditions, and occlusions, while explicitly depicting human hand and limb movements (Weinzaepfel et al., 2015; Si et al., 2018; Yan et al., 2018). Several recent studies exploit pose information and achieve state-of-the-art performance in fingerspelling-related tasks (Tanzer, 2024b; Fayyazsanavi et al., 2024; Moryossef et al., 2023). Hence, we use the key points extracted from DWPose (Yang et al., 2023) as video features to provide benchmark results.

RGB-based video feature representation: Several models directly extract features from sign videos, such as CNN-RNN-HMM network (Camgöz et al., 2018), S3D (Chen et al., 2022b) and I3D (Carreira & Zisserman, 2017). In the works (Albanie et al., 2020; Li et al., 2020a;b), I3D is used for sign video representation. To better adapt to SL dataset and capture the spatio-temporal information of signs, inspired by (Li et al., 2020b), we finetune I3D on a word-level sign language recognition dataset (Shen et al., 2024) and extract sign video features with different window widths and strides. Recent studies have shown that feeding raw RGB video directly into end-to-end models yields strong performance on various sign language tasks (Chen et al., 2022c; Min et al., 2021). Following this trend, we adopt raw video frames as input for our end-to-end models.

Table 3: Performance comparison (Letter Accuracy) on Fingerspelling Recognition (IFSR) across three data domains: News, Lab, and Web. "Full" refer to the combined dataset.

Table 4: Performance comparison on Fingerspelling Detection (FSD) and FSD-R tasks across three data domains. Average Precision (AP) at 0.5 IoU threshold for FSD (AP@IoU $_{0.5}$ ), and AP at 0.5 recognition accuracy threshold for FSD-R (AP@Acc $_{0.5}$ ).

Method	Train	Lette	er Accı	uracy (	(%)	Method	Train	A	P@IC	$00_{0.5}$		l A	AP@A	.cc <sub>0.5</sub>	
, , , , , , , , , , , , , , , , , , ,		News	Lab	Web	Full			News	Lab	Web	Full	News	Lab	Web	Full
CI Tours	Full	41.7 49.9		44.7 35.3		D. LOTMOTO	Full	31.1		27.2		15.5		14.8 8.5	26.9 17.8
SL-Transformer (Camgöz et al., 2020)	News Lab	31.2		34.9		Bi-LSTM CTC (Huang et al., 2015)	News Lab	10.0		23.8		21.6 5.0	15.6 71.1		36.3
(Camgoz et al., 2020)	Web	19.8		37.4		(Huang et al., 2015)	Web	13.1		26.1		6.5		13.3	
	Full	45.6		51.3			Full	35.2		32.2		19.6		15.6	
Iterative-Att	News	50.6			46.7	Modified R-C3D	News	47.9		25.0		23.2	16.2		18.9
(Shi et al., 2019)	Lab	30.2		30.3		(Xu et al., 2017)	Lab	11.9		17.0		6.1		10.8	
	Web	21.0	35.8	36.3	29.1		Web	15.9	40.9	30.1	28.7	7.0	14.5	14.4	11.1
	Full	56.4		60.1			Full	41.3		37.4		23.5		22.1	. —
MiCT-RANet	News	57.2		44.8		TS-FS-Det	News	53.6		34.0		29.3		19.3	
(Mahoudeau, 2020)	Lab	33.2		31.8		(Chen et al., 2022c)	Lab	12.2		18.7		7.4	77.9		40.7
	Web	22.9	38.6	42.5	31.7		Web	19.6	44.7	37.5	32.7	9.9	23.9	22.2	17.4
	Full	57.2	82.9	62.4	69.7		Full	48.6	79.7	41.6	62.7	25.4	68.7	26.8	45.9
TS-FS-Reg	News	59.2		50.4		MT-FS-Det	News	57.8		34.2		32.9		20.9	
(Chen et al., 2022c)	Lab	39.7		34.8		(Shi et al., 2021)	Lab	18.1		19.0		10.4		13.7	
	Web	24.1	36.8	46.2	31.6		Web	20.8	44.2	41.5	33.3	10.1	25.5	26.9	18.6
	Full	62.5	87.3	70.1	74.7		Full	53.9	82.7	47.3	66.9	33.7	76.3	30.2	53.5
FS-PoseNet	News	66.2		48.2		SL-Seg	News	60.0		38.8		35.9		24.2	
(Fayyazsanavi et al., 2024)	Lab	36.2		29.4		(Moryossef et al., 2023)	Lab	18.8		21.5		10.2		14.9	
	Web	26.5	47.2	51.4	38.0		Web	22.5	46.1	40.4	34.9	11.8	28.2	29.9	20.8

#### 5.2 Benchmark Results

In this section, we provide benchmark results of isolated fingerspelling recognition (IFSR), finger-spelling detection (FSD), fingerspelling detection followed by recognition (FSD-R) and fingerspelling recognition in context (FSR-Context) tasks on BANZ-FS.

**Isolated Fingerspelling Recognition (IFSR):** Table 3 presents a cross-domain evaluation of state-ofthe-art models on the IFSR task. The models are trained separately on four different subsets—News, Lab, Web, and the union of all (Full)—and evaluated across each domain. This setup allows for a detailed analysis of both in-domain performance (training and testing on the same source) and out-of-domain generalization (training on one domain, testing on another). Among all the models, FS-PoseNet consistently demonstrates the strongest cross-domain robustness. When trained on the Full set, it achieves the highest overall accuracy (74.7%), and outperforms other models by a large margin on challenging domains such as Web (38.0%). Notably, FS-PoseNet (Fayyazsanavi et al., 2024) trained on News alone generalizes well to Lab data (48.2%) and achieves the best News-to-News performance (66.2%), reflecting the benefit of its pose-guided Transformer architecture in capturing signer-invariant features. In contrast, SL-Transformer (Camgöz et al., 2020) and Iterative-Att (Shi et al., 2019) show limited generalization ability. Their performance drops significantly when evaluated on unseen domains, especially on Web videos where visual variability is high. MiCT-RANet (Mahoudeau, 2020) and TS-FS-Reg (Chen et al., 2022c) achieve stronger generalization than early models, particularly when trained on the Full set, with accuracies of 68.6% and 69.7% respectively. TS-FS-Reg (Chen et al., 2022c) benefits from dual-modality inputs, which help mitigate overfitting to domain-specific appearance. Overall, the results reveal that while most models perform well on the domain they are trained on—especially Lab, which offers controlled recording conditions—cross-domain generalization remains a significant challenge. FS-PoseNet (Fayyazsanavi et al., 2024) stands out by consistently maintaining strong performance across all domains, making it particularly promising for deployment in real-world scenarios with diverse video sources.

**Fingerspelling Detection (FSD):** The FSD results in Table 4 show notable variation across domains. SL-Seg (Moryossef et al., 2023) achieves the best overall detection performance, particularly excelling on the Web domain (47.3%), where other models generally struggle. This suggests that frame-level BIO tagging with pose-based cues provides more robust temporal boundary modeling than proposal-based or regression-based methods. While MT-FS-Det (Shi et al., 2021) and TS-FS-Det (Chen et al., 2022c) perform competitively on News and Lab subsets, their generalization to noisy Web data is limited. In contrast, performance of earlier approaches, such as Modified R-C3D (Xu et al., 2017)

Figure 5: Case study comparing IFSR, FSD, and FSD-R on fingerspelling sequences.

and Bi-LSTM CTC (Huang et al., 2015), is much inferior, highlighting the importance of structured temporal representations and boundary-aware learning for reliable fingerspelling localization.

**Fingerspelling Detection followed by Recognition (FSD-R):** The FSD-R results evaluate the quality of detected segments by measuring whether they are both correctly localized and correctly recognized. In our setup, each predicted segment is fed into a pre-trained FS-PoseNet (Fayyazsanavi et al., 2024) recognizer, and is counted as correct only if the recognition accuracy exceeds 50%. As shown in Table 4, we observe a clear performance gap between detection and FSD-R. Even well-localized segments often fail to reach the required recognition threshold, especially in the Web domain. SL-Seg (Moryossef et al., 2023) achieves the highest overall AP@Acc (53.5%), yet still struggles on the Web subset (20.8%), underscoring the difficulty of maintaining segment quality under noisy conditions. These results emphasize that effective detection must also consider recognizability, motivating future work on recognition-aware detection or joint optimization approaches.

Fingerspelling Recognition in Context (FSR-Context): Following the protocol introduced in (Tanzer, 2024b), we extract fingerspelled spans from predicted translations and compute character-level Letter Accuracy based on alignment with annotated ground-truth phrases. We conduct our evaluation on expanded Auslan News dataset, which contains 18,604 sentence-level sign language videos, 13,208 of which include fingerspelled terms. We first evaluate a state-of-the-art gloss-free SLT model (Zhou et al., 2023) on sentence-level sign language videos that contain fingerspelled content. The model achieves a Letter Accuracy of 16.4% on the FSR-Context task. We then compare two Transformer-based translation models: T5 (Raffel et al., 2020) (subword tokenization) and ByT5 (Xue et al., 2022) (character-level tokenization). Results show that ByT5 outperforms T5, achieving a Letter Accuracy of 25.8% compared to just 10.2% for T5. These findings are consistent with previous work (Tanzer, 2024b) and suggest that character-level tokenization offers substantial benefits for preserving the spelling of out-of-vocabulary words in translation output. The details of the expanded Auslan News dataset are provided in the Appendix Section C.2.

#### 5.3 CASE STUDY

In Figure 5, we present several case studies across IFSR, FSD, and FSD-R settings. Some segments are correctly detected and recognized. However, rapid fingerspelling challenges the recognizer (*e.g.*, two P's within 8 frames), and loose detection boundaries cause unrelated gestures to be included, resulting in spurious predictions like "1". These errors highlight the compound difficulty of accurate detection and recognition under natural signing conditions. Additional case studies are provided in the Appendix Section H.

# 6 CONCLUSION

In this work, we introduce **BANZ-FS**, a large-scale and richly annotated dataset dedicated to finger-spelling in the BANZSL. Our dataset is constructed from three diverse sources that cover a broad spectrum of signing tempos and registers, from formal broadcast interpretation to everyday interaction. BANZ-FS features over 35,000 aligned fingerspelling instances with multi-level annotations, including temporal segments, character sequences, lexical forms, and full-sentence transcriptions. We benchmark several fingerspelling-related tasks on BANZ-FS, including fingerspelling detection, isolated fingerspelling recognition, and fingerspelling recognition in context. To support contextual FS evaluation, we also extend the Auslan-Daily News subset with three times more aligned content. Through analysis and experiments, we demonstrate the challenges and opportunities posed by fingerspelling in BANZSL, particularly in the context of two-handed systems, self-occlusion, rapid transitions, and lexical variability. We hope that BANZ-FS will serve as a valuable resource for advancing sign language understanding, and encourage further research on fingerspelling phenomena across diverse linguistic and visual contexts.

# ETHICS STATEMENT

This work involves the curation of BANZ-FS, a large-scale dataset for BANZSL fingerspelling. We have carefully considered the ethical implications of data collection, annotation, and release, in line with the ICLR Code of Ethics.

**Human Subjects & Consent.** All data collected in the *Lab Recordings* subset are conducted under ethical oversight in a safe, supervised laboratory environment. Each participant (or guardian, in the case of minors) signs a detailed consent form (Appendix Section D) stating that their facial expressions and hand gestures may be recorded for research use only, without commercial redistribution. Participation is voluntary, and participants can withdraw at any time. The study protocol, consent procedure, and data handling plan are reviewed by the *University's Research Ethics Committee*, which classifies the study as ethically exempt under its guidelines. We maintain signed consent records and perform post-recording verification, ensuring adherence to consent terms.

**Compensation.** All contributors are fairly compensated: general volunteers at AUD \$40/hour, and Deaf signers and Auslan experts at AUD \$100/hour, in line with institutional and regional standards. Approximately 500 hours of paid annotation work are carried out under formal contract.

**Privacy & Anonymization.** All participants explicitly consent to the public release of their (unblurred) recordings for academic use. A withdrawal and anonymization protocol is in place: we apply face-blurring (using deface) upon participant request, and delete data entirely if consent is withdrawn. Future releases also provide 2D/3D pose annotations to support privacy-preserving research. No personally identifiable information (PII) or sensitive data (health or financial information) is collected.

**Copyright & Licensing.** All *web-sourced* and *broadcast* segments are included under appropriate non-commercial licenses (CC BY-NC-SA 4.0) (Shen et al., 2023) or explicit permission for research use. The dataset is released under the same license, along with an End-User License Agreement (EULA) that prohibits commercial exploitation, re-identification, and surveillance use. A takedown-request email is provided for removal or anonymization requests.

**Fairness & Representativeness.** We report signer demographics (gender, age, region, race) across all three data sources (Appendix Section C.6). While Auslan data dominates, the BANZSL alphabet is shared across dialects, and cross-dialect evaluation shows good generalization. We acknowledge remaining imbalances and plan to mine additional BSL/NZSL data and incorporate community feedback in future releases.

**Responsible Use.** We include a Responsible Use Statement with the dataset that explicitly prohibits its deployment in surveillance, biometric identification, or other sensitive decision-making contexts without further ethical review. Our release aims to support inclusive, equitable research benefiting the BANZSL and Deaf communities.

# REPRODUCIBILITY STATEMENT

We take reproducibility seriously, and due to the current stage of the review process, we provide an anonymous GitHub repository that includes some data samples (due to storage limitations), data storage structure, and annotation files. Our main dataset repository and Google Drive link will be released after the review process. This ensures that anyone can regenerate exactly the same dataset version used in our experiments.

For benchmarking, we exclusively use publicly available models and follow their original hyperparameter settings without any modification. This guarantees fair and consistent comparison across methods. Detailed dataset statistics, preprocessing steps, and quality control procedures are provided in Section 3. For more experiment details, please refer to Appendix Section F and the anonymous GitHub repositor  $\mathbf{O}$  BANZ-FS.

### REFERENCES

Samuel Albanie, Gül Varol, Liliane Momeni, Triantafyllos Afouras, Joon Son Chung, Neil Fox, and Andrew Zisserman. Bsl-1k: Scaling up co-articulated sign language recognition using mouthing

cues. In European conference on computer vision, pp. 35–53. Springer, 2020.

- Matyáš Boháček and Marek Hrúz. Sign pose-based transformer for word-level sign language recognition. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) Workshops*, pp. 182–191, January 2022.
- Necati Cihan Camgöz, Simon Hadfield, Oscar Koller, Hermann Ney, and Richard Bowden. Neural sign language translation. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pp. 7784—7793. Computer Vision Foundation / IEEE Computer Society, 2018. doi: 10.1109/CVPR. 2018.00812. URL http://openaccess.thecvf.com/content\_cvpr\_2018/html/Camgoz\_Neural\_Sign\_Language\_CVPR\_2018\_paper.html.
- Necati Cihan Camgöz, Oscar Koller, Simon Hadfield, and Richard Bowden. Sign language transformers: Joint end-to-end sign language recognition and translation. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020, pp. 10020–10030. Computer Vision Foundation / IEEE, 2020. doi: 10.1109/CVPR42600.2020.01004. URL https://openaccess.thecvf.com/content\_CVPR\_2020/html/Camgoz\_Sign\_Language\_Transformers\_Joint\_End-to-End\_Sign\_Language\_Recognition\_and\_Translation\_CVPR\_2020\_paper.html.
- João Carreira and Andrew Zisserman. Quo vadis, action recognition? A new model and the kinetics dataset. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pp. 4724–4733. IEEE Computer Society, 2017. doi: 10.1109/CVPR.2017.502. URL https://doi.org/10.1109/CVPR.2017.502.
- Yutong Chen, Fangyun Wei, Xiao Sun, Zhirong Wu, and Stephen Lin. A simple multi-modality transfer learning baseline for sign language translation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pp. 5110–5120. IEEE, 2022a. doi: 10.1109/CVPR52688.2022.00506. URL https://doi.org/10.1109/CVPR52688.2022.00506.
- Yutong Chen, Fangyun Wei, Xiao Sun, Zhirong Wu, and Stephen Lin. A simple multi-modality transfer learning baseline for sign language translation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pp. 5110–5120. IEEE, 2022b. doi: 10.1109/CVPR52688.2022.00506. URL https://doi.org/10.1109/CVPR52688.2022.00506.
- Yutong Chen, Ronglai Zuo, Fangyun Wei, Yu Wu, Shujie Liu, and Brian Mak. Two-stream network for sign language recognition and translation. In *NeurIPS*, 2022c. URL http://papers.nips.cc/paper\_files/paper/2022/hash/6cd3ac24cdb789beeaa9f7145670fcae-Abstract-Conference.html.
- Aashaka Desai, Lauren Berger, Fyodor Minakov, Nessa Milano, Chinmay Singh, Kriston Pumphrey, Richard E. Ladner, Hal Daumé III, Alex X. Lu, Naomi Caselli, and Danielle Bragg. ASL citizen: A community-sourced dataset for advancing isolated sign language recognition. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023, 2023. URL http://papers.nips.cc/paper\_files/paper/2023/hash/f29cf8f8b4996a4a453ef366cf496354-Abstract-Datasets\_and\_Benchmarks.html.
- Amanda Cardoso Duarte, Shruti Palaskar, Lucas Ventura, Deepti Ghadiyaram, Kenneth De-Haan, Florian Metze, Jordi Torres, and Xavier Giró-i-Nieto. How2sign: A large-scale multimodal dataset for continuous american sign language. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021, virtual, June 19-25, 2021*, pp. 2735–2744. Computer Vision Foundation / IEEE, 2021. doi: 10.1109/CVPR46437.2021.00276. URL https://openaccess.thecvf.com/content/CVPR2021/html/Duarte\_How2Sign\_A\_Large-Scale\_Multimodal\_Dataset\_for\_Continuous\_American\_Sign\_Language\_CVPR\_2021\_paper.html.

- Hao-Shu Fang, Shuqin Xie, Yu-Wing Tai, and Cewu Lu. RMPE: Regional multi-person pose estimation. In *ICCV*, 2017.
  - Hao-Shu Fang, Jiefeng Li, Hongyang Tang, Chao Xu, Haoyi Zhu, Yuliang Xiu, Yong-Lu Li, and Cewu Lu. Alphapose: Whole-body regional multi-person pose estimation and tracking in real-time. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022.
  - Pooya Fayyazsanavi, Negar Nejatishahidin, and Jana Košecká. Fingerspelling posenet: Enhancing fingerspelling translation with pose-based transformer models. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 1120–1130, 2024.
- Manfred Georg, Garrett Tanzer, Saad Hassan, Maximus Shengelia, Esha Uboweja, Sam Sepah, Sean Forbes, and Thad Starner. Fsboard: Over 3 million characters of asl fingerspelling collected via smartphones. *arXiv preprint arXiv:2407.15806*, 2024.
- Lianyu Hu, Liqing Gao, Zekang Liu, and Wei Feng. Dynamic spatial-temporal aggregation for skeleton-aware sign language recognition. In Nicoletta Calzolari, Min-Yen Kan, Véronique Hoste, Alessandro Lenci, Sakriani Sakti, and Nianwen Xue (eds.), *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation, LREC/COLING 2024*, 20-25 May, 2024, Torino, Italy, pp. 5450–5460. ELRA and ICCL, 2024. URL https://aclanthology.org/2024.lrec-main.484.
- Jie Huang, Wengang Zhou, Houqiang Li, and Weiping Li. Attention-based 3d-cnns for large-vocabulary sign language recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 29(9):2822–2832, 2018.
- Zhiheng Huang, Wei Xu, and Kai Yu. Bidirectional LSTM-CRF models for sequence tagging. *CoRR*, abs/1508.01991, 2015. URL http://arxiv.org/abs/1508.01991.
- Songyao Jiang, Bin Sun, Lichen Wang, Yue Bai, Kunpeng Li, and Yun Fu. Skeleton aware multi-modal sign language recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, 2021a.
- Songyao Jiang, Bin Sun, Lichen Wang, Yue Bai, Kunpeng Li, and Yun Fu. Sign language recognition via skeleton-aware multi-model ensemble. *CoRR*, abs/2110.06161, 2021b. URL https://arxiv.org/abs/2110.06161.
- Taehwan Kim, Jonathan Keane, Weiran Wang, Hao Tang, Jason Riggle, Gregory Shakhnarovich, Diane Brentari, and Karen Livescu. Lexicon-free fingerspelling recognition from video: Data, models, and signer adaptation. *Computer Speech & Language*, 46:209–232, 2017.
- Dongxu Li, Cristian Rodriguez, Xin Yu, and Hongdong Li. Word-level deep sign language recognition from video: A new large-scale dataset and methods comparison. In *The IEEE Winter Conference on Applications of Computer Vision*, pp. 1459–1469, 2020a.
- Dongxu Li, Chenchen Xu, Xin Yu, Kaihao Zhang, Benjamin Swift, Hanna Suominen, and Hongdong Li. Tspnet: Hierarchical feature learning via temporal semantic pyramid for sign language translation. In Hugo Larochelle, Marc' Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin (eds.), Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual, 2020b. URL https://proceedings.neurips.cc/paper/2020/hash/8c00dee24c9878fea090ed070b44flab-Abstract.html.
- Dongxu Li, Xin Yu, Chenchen Xu, Lars Petersson, and Hongdong Li. Transferring cross-domain knowledge for video sign language recognition. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020, pp. 6204-6213. Computer Vision Foundation / IEEE, 2020c. doi: 10.1109/CVPR42600.2020.00624. URL https://openaccess.thecvf.com/content\_CVPR\_2020/html/Li\_Transferring\_Cross-Domain\_Knowledge\_for\_Video\_Sign\_Language\_Recognition\_CVPR\_2020\_paper.html.
- Jiefeng Li, Can Wang, Hao Zhu, Yihuan Mao, Hao-Shu Fang, and Cewu Lu. Crowdpose: Efficient crowded scenes pose estimation and a new benchmark. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10863–10872, 2019.

- Linjun Li, Tao Jin, Xize Cheng, Ye Wang, Wang Lin, Rongjie Huang, and Zhou Zhao. Contrastive token-wise meta-learning for unseen performer visual temporal-aligned translation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 10993–11007, 2023.
  - Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. In Lluís Màrquez, Chris Callison-Burch, Jian Su, Daniele Pighin, and Yuval Marton (eds.), *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pp. 1412–1421. The Association for Computational Linguistics, 2015. doi: 10.18653/v1/d15-1166. URL https://doi.org/10.18653/v1/d15-1166.
  - Florent Mahoudeau. Mict-ranet for real-time asl fingerspelling video recognition. https://github.com/fmahoudeau/MiCT-RANet-ASL-FingerSpelling, 2020.
  - Yuecong Min, Aiming Hao, Xiujuan Chai, and Xilin Chen. Visual alignment constraint for continuous sign language recognition. In *proceedings of the IEEE/CVF international conference on computer vision*, pp. 11542–11551, 2021.
  - Amit Moryossef, Ioannis Tsochantaridis, Roee Aharoni, Sarah Ebling, and Srini Narayanan. Realtime sign language detection using human pose estimation. In *European Conference on Computer Vision*, pp. 237–248. Springer, 2020.
  - Amit Moryossef, Zifan Jiang, Mathias Müller, Sarah Ebling, and Yoav Goldberg. Linguistically motivated sign language segmentation. *arXiv preprint arXiv:2310.13960*, 2023.
  - Carol A. Padden. The asl lexicon. pp. 1:33-51, 1998.
  - Katerina Papadimitriou, Galini Sapountzaki, Kyriaki Vasilaki, Eleni Efthimiou, Stavroula-Evita Fotinea, and Gerasimos Potamianos. A large corpus for the recognition of greek sign language gestures. *Computer Vision and Image Understanding*, 249:104212, 2024.
  - KR Prajwal, Hannah Bull, Liliane Momeni, Samuel Albanie, Gül Varol, and Andrew Zisserman. Weakly-supervised fingerspelling recognition in british sign language videos. *arXiv preprint arXiv:2211.08954*, 2022.
  - Nicolas Pugeault and Richard Bowden. Spelling it out: Real-time asl fingerspelling recognition. In 2011 IEEE International conference on computer vision workshops (ICCV workshops), pp. 1114–1119. Ieee, 2011.
  - Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67, 2020.
  - Mike Schuster and Kuldip K Paliwal. Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, 45(11):2673–2681, 1997.
  - Xin Shen, Shaozu Yuan, Hongwei Sheng, Heming Du, and Xin Yu. Auslan-daily: Australian sign language translation for daily communication and news. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023, 2023. URL http://papers.nips.cc/paper\_files/paper/2023/hash/feb34ce77fc8b94c85d12e608b23ce67-Abstract-Datasets\_and\_Benchmarks.html.
  - Xin Shen, Heming Du, Hongwei Sheng, Shuyun Wang, Hui Chen, Huiqiang Chen, Zhuojie Wu, Xiaobiao Du, Jiaying Ying, Ruihan Lu, et al. Mm-wlauslan: Multi-view multi-modal word-level australian sign language recognition dataset. *arXiv preprint arXiv:2410.19488*, 2024.
  - Xin Shen, Heming Du, Hongwei Sheng, Lincheng Li, and Kaihao Zhang. Auslanweb: A scalable web-based australian sign language communication system for deaf and hearing individuals. In Guodong Long, Michale Blumestein, Yi Chang, Liane Lewin-Eytan, Zi Helen Huang, and Elad Yom-Tov (eds.), *Proceedings of the ACM on Web Conference 2025, WWW 2025, Sydney, NSW, Australia, 28 April 2025- 2 May 2025*, pp. 5212–5223. ACM, 2025. doi: 10.1145/3696410.3714525. URL https://doi.org/10.1145/3696410.3714525.

- Hongwei Sheng, Xin Shen, Heming Du, Hu Zhang, Zi Huang, and Xin Yu. Ai empowered auslan learning for parents of deaf children and children of deaf adults. *AI and Ethics*, pp. 1–11, 2024.
- Bowen Shi, Aurora Martinez Del Rio, Jonathan Keane, Jonathan Michaux, Diane Brentari, Greg Shakhnarovich, and Karen Livescu. American sign language fingerspelling recognition in the wild. In 2018 IEEE Spoken Language Technology Workshop, SLT 2018, Athens, Greece, December 18-21, 2018, pp. 145–152. IEEE, 2018. doi: 10.1109/SLT.2018.8639639. URL https://doi.org/10.1109/SLT.2018.8639639.
- Bowen Shi, Aurora Martinez Del Rio, Jonathan Keane, Diane Brentari, Greg Shakhnarovich, and Karen Livescu. Fingerspelling recognition in the wild with iterative visual attention. In *Proceedings* of the IEEE/CVF International Conference on Computer Vision, pp. 5400–5409, 2019.
- Bowen Shi, Diane Brentari, Greg Shakhnarovich, and Karen Livescu. Fingerspelling detection in american sign language. In *IEEE Conference on Computer Vision and Pattern Recognition*, *CVPR 2021*, *virtual*, *June 19-25*, *2021*, pp. 4166–4175. Computer Vision Foundation / IEEE, 2021. doi: 10.1109/CVPR46437.2021.00415. URL https://openaccess.thecvf.com/content/CVPR2021/html/Shi\_Fingerspelling\_Detection\_in\_American\_Sign\_Language\_CVPR\_2021\_paper.html.
- Bowen Shi, Diane Brentari, Gregory Shakhnarovich, and Karen Livescu. Open-domain sign language translation learned from online video. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (eds.), Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022, pp. 6365–6379. Association for Computational Linguistics, 2022. URL https://aclanthology.org/2022.emnlp-main.427.
- Chenyang Si, Ya Jing, Wei Wang, Liang Wang, and Tieniu Tan. Skeleton-based action recognition with spatial reasoning and temporal stack learning. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss (eds.), Computer Vision ECCV 2018 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part I, volume 11205 of Lecture Notes in Computer Science, pp. 106–121. Springer, 2018. doi: 10.1007/978-3-030-01246-5\\_7. URL https://doi.org/10.1007/978-3-030-01246-5\_7.
- Thad Starner, Sean Forbes, Matthew So, David Martin, Rohit Sridhar, Gururaj Deshpande, and et al. Popsign ASL v1.0: An isolated american sign language dataset collected via smartphones. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023, 2023. URL http://papers.nips.cc/paper\_files/paper/2023/hash/00dada608b8db212ea7d9d92b24c68de-Abstract-Datasets\_and\_Benchmarks.html.
- Garrett Tanzer. Fleurs-asl: Including american sign language in massively multilingual multitask evaluation. *arXiv preprint arXiv:2408.13585*, 2024a.
- Garrett Tanzer. Fingerspelling within sign language translation. arXiv preprint arXiv:2408.07065, 2024b.
- Garrett Tanzer and Biao Zhang. Youtube-sl-25: A large-scale, open-domain multilingual sign language parallel corpus. *arXiv preprint arXiv:2407.11144*, 2024.
- Gabriel Tsechpenakis, Dimitris N. Metaxas, and Carol Neidle. Learning-based dynamic coupling of discrete and continuous trackers. *Comput. Vis. Image Underst.*, 104(2-3):140–156, 2006a. doi: 10. 1016/J.CVIU.2006.07.009. URL https://doi.org/10.1016/j.cviu.2006.07.009.
- Gabriel Tsechpenakis, Dimitris N Metaxas, Carol Neidle, and Olympia Hadjiliadis. Robust online change-point detection in video sequences. In *Proceedings of the 2006 Conference on Computer Vision and Pattern Recognition Workshop*, pp. 155–161, 2006b.
- Dave Uthus, Garrett Tanzer, and Manfred Georg. Youtube-asl: A large-scale, open-domain american sign language-english parallel corpus. *Advances in Neural Information Processing Systems*, 36: 29029–29047, 2023.

- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
  - Philippe Weinzaepfel, Zaïd Harchaoui, and Cordelia Schmid. Learning to track for spatio-temporal action localization. In 2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015, pp. 3164–3172. IEEE Computer Society, 2015. doi: 10.1109/ICCV.2015.362. URL https://doi.org/10.1109/ICCV.2015.362.
  - Huijuan Xu, Abir Das, and Kate Saenko. R-C3D: region convolutional 3d network for temporal activity detection. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pp. 5794–5803. IEEE Computer Society, 2017. doi: 10.1109/ICCV.2017.617. URL https://doi.org/10.1109/ICCV.2017.617.
  - Linting Xue, Aditya Barua, Noah Constant, Rami Al-Rfou, Sharan Narang, Mihir Kale, Adam Roberts, and Colin Raffel. Byt5: Towards a token-free future with pre-trained byte-to-byte models. *Transactions of the Association for Computational Linguistics*, 10:291–306, 2022.
  - Sijie Yan, Yuanjun Xiong, and Dahua Lin. Spatial temporal graph convolutional networks for skeleton-based action recognition. In Sheila A. McIlraith and Kilian Q. Weinberger (eds.), *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence*, pp. 7444–7452. AAAI Press, 2018. URL https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/17135.
  - Hee-Deok Yang and Seong-Whan Lee. Simultaneous spotting of signs and fingerspellings based on hierarchical conditional random fields and boostmap embeddings. *Pattern Recognit.*, 43(8):2858–2870, 2010. doi: 10.1016/J.PATCOG.2010.03.007. URL https://doi.org/10.1016/j.patcog.2010.03.007.
  - Zhendong Yang, Ailing Zeng, Chun Yuan, and Yu Li. Effective whole-body pose estimation with two-stages distillation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 4210–4220, 2023.
  - Polina Yanovich, Carol Neidle, and Dimitris N. Metaxas. Detection of major ASL sign types in continuous signing for ASL recognition. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Sara Goggi, Marko Grobelnik, Bente Maegaard, Joseph Mariani, Hélène Mazo, Asunción Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Tenth International Conference on Language Resources and Evaluation LREC 2016, Portorož, Slovenia, May 23-28, 2016.* European Language Resources Association (ELRA), 2016. URL http://www.lrec-conf.org/proceedings/lrec2016/summaries/714.html.
  - Aoxiong Yin, Tianyun Zhong, Li Tang, Weike Jin, Tao Jin, and Zhou Zhao. Gloss attention for gloss-free sign language translation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2551–2562, 2023.
  - Benjia Zhou, Zhigang Chen, Albert Clapés, Jun Wan, Yanyan Liang, Sergio Escalera, Zhen Lei, and Du Zhang. Gloss-free sign language translation: Improving from visual-language pretraining. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 20871–20881, 2023.
  - Hao Zhou, Wengang Zhou, Weizhen Qi, Junfu Pu, and Houqiang Li. Improving sign language translation with monolingual data by sign back-translation. In *IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2021, virtual, June 19-25, 2021, pp. 1316–1325. Computer Vision Foundation / IEEE, 2021. doi: 10.1109/CVPR46437.2021.00137. URL https://openaccess.thecvf.com/content/CVPR2021/html/Zhou\_Improving\_Sign\_Language\_Translation\_With\_Monolingual\_Data\_by\_Sign\_Back-Translation\_CVPR\_2021\_paper.html.
  - Ronglai Zuo, Fangyun Wei, and Brian Mak. Natural language-assisted sign language recognition. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2023, Vancouver, BC, Canada, June 17-24, 2023*, pp. 14890–14900. IEEE, 2023. doi: 10.1109/CVPR52729.2023.01430. URL https://doi.org/10.1109/CVPR52729.2023.01430.

This appendix is organized as follows:

810

811 812

813

814

815 816

817

818

819

820 821

823

824

825

827

828 829

830

831

832

833

834

835

836

837

838

839

840

841

842

843

844

845 846 847

848 849

850

851

852

853

854

855

856

858

859

860

861

862

863

- BROADER IMPACT (Section A).
  - Limitations and Future Work (Section B).
  - BUILDING BANZ-FS (Section C).
  - CONSENT FORM FOR BANZ-FS RECORDING (Section D).
  - MORE DETAILS FOR VIDEO REPRESENTATION (Section E).
  - EXPERIMENTAL SETTINGS (Section F).
  - THE BASELINE OF AUSLAN-DAILY NEWS V2 (Section G).
  - CASE STUDY FOR BANZ-FS FINGERSPELLING DETECTION AND RECOGNITION (Section H).
  - CASE STUDY FOR AUSLAN-DAILY NEWS SIGN LANGUAGE TRANSLATION (Section I).
  - LLM USAGE STATEMENT (Section J).

# A BROADER IMPACT

The BANZ-FS dataset addresses a critical gap in the sign language research community by focusing on the underrepresented two-handed fingerspelling systems of BANZSL (British, Australian, and New Zealand Sign Languages). This work has the potential to significantly improve accessibility technologies for Deaf and hard-of-hearing communities across multiple English-speaking regions. By supporting robust research on fingerspelling detection and recognition, BANZ-FS can contribute to the development of real-time translation systems, assistive educational tools for sign language learners, and inclusive communication platforms. Importantly, the dataset includes real-world scenarios drawn from news, vlogs, and lab settings, thus promoting domain generalization in practical applications. However, as with any dataset involving human subjects, privacy, representation, and consent are essential considerations. All included video data are sourced from publicly available content or recorded with informed consent. Nevertheless, we acknowledge that biases may still exist, such as overrepresentation of Auslan compared to BSL or NZSL, and uneven distribution of fingerspelled letters. Future work should address these issues through targeted data collection and model adaptation techniques. Finally, while the goal is to aid accessibility, there is also a risk of misuse—such as surveillance or unauthorized profiling using sign language recognition systems. We strongly encourage researchers and practitioners to follow ethical guidelines and collaborate closely with Deaf communities when deploying models trained on BANZ-FS.

# B LIMITATION AND FUTURE WORK

Our work has two primary limitations. Letter Frequency Imbalance. Letter imbalance exists in the dataset—frequent characters like "N", "S", "E", and "W" dominate due to their linguistic role in directional terms, while rarer letters such as "X" and "J" are significantly underrepresented. Such skew is common in natural language corpora and other fingerspelling datasets; for example, in ChicagoFSWild+ (Shi et al., 2019), the most frequent letters "A", "E", and "O" each appear over 20K times, whereas the rarest letters "Z" and "Q" appear only 494 and 311 times, respectively. To mitigate this effect, we carefully balanced the validation and test splits to ensure fair representation of low-frequency letters. As shown in Table 5, several characters and digits occur fewer than 1,000 times, but we ensure their presence across all splits. Our dataset design further supports alleviation of long-tail issues: the Lab Recordings subset enables targeted collection of underrepresented characters, and our BANZ-FS-trained detector can be used to mine additional candidate instances from unlabeled videos. In future work, we plan to explore sign language generation techniques to synthetically augment low-frequency letters and improve overall letter coverage. **Dialect Imbalance.** There is a clear dialect imbalance within the BANZSL subset: the data is heavily skewed toward Auslan, with BSL and NZSL contributions being relatively limited. Nevertheless, all three dialects share the same two-handed fingerspelling alphabet, and as shown in Table 3 and Table 4, models trained on the Auslan subset generalize well to BSL and NZSL web data. In future work, we will use our trained

Table 5: Frequency of underrepresented letters and digits (total count < 1,000) across train/valid/test splits in BANZ-FS.

Split	FS-"8"	FS-"7"	FS-"6"	FS-"0"	FS-"X"	FS-"9"	FS-"J"
Train	596	538	503	464	348	324	271
Valid	98	89	76	84	56	42	29
Test	114	107	85	79	66	54	39
Total	808	734	664	627	470	420	339

BANZ-FS detector to mine additional BSL/NZSL clips from broadcast and web sources, thereby improving dialectal diversity and representation.

Beyond data, we also plan to investigate recognition-aware detection models that jointly optimize for temporal localization and fingerspelling accuracy. In addition, we aim to explore context-conditioned models that leverage sentence-level semantics to improve recognition of ambiguous or incomplete fingerspelling segments.

# C Building BANZ-FS

In this section, we explain the various stages of data processing and labelling in detail for preparing BANZ-FS, from collecting sources to storing final data.

#### C.1 DATA PROCESSING AND LABELLING

Although the original Auslan videos are accompanied by English subtitles, the sentence boundaries in the subtitles are often misaligned with the actual signing segments due to differences in grammar, timing, and expression modalities between sign and spoken languages. To address this, we perform a sentence-level alignment procedure. First, we clean the raw subtitles by merging incomplete fragments (*e.g.*, those ending with commas), splitting multiple complete sentences within a single time interval, and removing non-informative expressions such as interjections.

As delineated in Section 3.1, we employ three distinct operations for subtitle cleaning (Shen et al., 2023). Here, we present a few representative examples:

• Incomplete subtitles:

[00:00:07,480]-[00:00:10,160] Today, a flood emergency warning issued for [00:00:10,200]-[00:00:18,720] Tasmania's River Derwent.

Revise:

[00:00:07,480]-[00:00:18,720] Today, a flood emergency warning issued for Tasmania's River Derwent.

• Several complete subtitles that appear within a time interval:

[00:00:54,520]-[00:00:59,320] Hello and welcome to ABC News. I'm Gemma Veness. Revise:

[00:00:54,520]-[00:00:59,320] Hello and welcome to ABC News. [00:00:54,520]-[00:00:59,320] I'm Gemma Veness.

• Complete sentence that only contains modal particles: [00:23:42,240]-[00:23:43,080] Ha-Ha.

Revise:

Remove this subtitle.

After preprocessing, we obtain clean sentences. Then, Auslan experts manually align each sentence with its corresponding video segment. As illustrated in Figure 6, this alignment is conducted at the sentence level, taking into account both audio-aligned and sign-aligned timelines. The signer is first tracked, followed by precise segmentation of each sentence's temporal span within the video. This results in temporally grounded video—sentence pairs, which are essential for training robust and accurate sign language translation (SLT) models.

In addition to sentence-level alignment, we also annotate fine-grained elements such as fingerspelling segments and lexical boundaries. Fingerspelling alignment identifies the exact start and end times

Figure 6: Illustration of sentence-level alignment. The signer is first tracked, followed by audio and sign alignment of the subtitle. Sentence segments, fingerspelling intervals, and lexical boundaries are then precisely annotated.

Table 6: Key statistics of Auslan-Daily New V1 and Auslan-Daily New V2. OOV: out-of-vocabulary. Singleton: words that only occur once in the training dataset.

Sub-Dataset	Auslan-Dail	ly News V1 (S	hen et al., 2023)	Ausla	n-Daily New	s V2	
Domain/Topic Video Resolution@FPS		ews & Docum (720/1920×10		12	News 280×720@25	5	
Split	Train	Dev	Test	Train	Dev	Test	Total
Segments	9,665	700	700	16,604	1,000	1,000	29,669
Signers	18	17	17	24	22	19	27
Frames	2,072,475	144,819	142,893	2,925,597	157,619	149,984	5,593,387
Vocab.	12,346	2,872	2,885	13,767	3,020	3,010	15,976
Tot. words	163,268	11,376	11,530	277,699	14,343	14,408	492,624
Tot. OOVs	-	326	304	-	217	224	475
Singletons	5,267	-	-	6,110	-	-	8,039

of letter-by-letter signing, which often corresponds to proper nouns or unseen words. Lexicon alignment further breaks down the sentence into semantically significant units such as named entities or domain-specific terms. These multi-level annotations enable a richer understanding of signed content and facilitate downstream tasks such as fingerspelling recognition and detection.

#### C.2 AUSLAN-DAILY NEWS V2

Auslan experts manually annotate sentence-level temporal boundaries within the Auslan-Daily News videos to accurately align signed utterances with their corresponding English subtitles. This alignment process not only corrected mismatches between spoken captions and signing segments but also ensured each signed sentence was temporally grounded with high precision. As a result of this effort, we substantially expanded the original Auslan-Daily News subset and release it as a new version, termed **Auslan-Daily News V2**.

Table 6 presents a detailed comparison between the Auslan-Daily News V1 and V2 sub-datasets in terms of data volume, diversity, and vocabulary statistics. V2 significantly expands upon V1, featuring nearly twice the number of annotated segments (29,669 vs. 11,065), frames (5.6M vs. 2.3M), and total words (492,624 vs. 188,774). It also includes a larger vocabulary size (15,976 vs. 12,346) and more signers (27 vs. 18), reflecting improved linguistic and signer diversity. The increase in out-of-vocabulary (OOV) words and singletons further illustrates the dataset's long-tail lexical distribution, which poses challenges but also fosters better generalization in sign language translation and recognition models.

# C.3 FINGERSPELLING ANNOTATION GUIDELINES.

To ensure consistency and accuracy in fingerspelling (FS) labeling, we adopt a structured three-step annotation protocol:

1. **Temporal Identification:** Annotators first review the entire video and identify all time intervals where fingerspelling occurs. These segments are typically characterized by rapid

Table 7: Examples of fingerspelling (FS) instances and their corresponding aligned content.

Sentence	1	Fingerspelled Sequence	1	Aligned Text
The growth is going to have to rely heavily on <b>equity</b> students wanting to go to university.		EQTITY		equity
We've used Variety in the past for some of his <b>equipment</b> and support.	1	E Q	Ī	equipment
The Western Bulldogs beaten Greater Western Sydney.		G W S		Greater Western Sydney
Irishwoman Leona Maguire has a one-shot lead heading.		MAQUIRE	1	Maguire
Steven miles did a good job as leader.		MIIMILES	-	miles
He said he will get a job.		ВОВ	Ī	No aligned word

handshapes corresponding to individual alphabet letters, often used to spell out names, technical terms, or out-of-vocabulary words.

- 2. **Character-Level Transcription:** Within each identified FS segment, annotators transcribe the fingerspelled content into a sequence of characters (A–Z), ensuring the character sequence reflects the exact order and repetition observed in the signing. Ambiguous or occluded handshapes may be annotated with a special token (e.g., '\*') when necessary.
- 3. **English Alignment:** After obtaining the character-level transcription, annotators check whether the transcribed fingerspelling sequence corresponds to any English word or phrase within the aligned sentence. If a match is found, the FS sequence is linked to the corresponding word or phrase. If no such alignment exists (e.g., due to fingerspelling of foreign names or uncommon entities), the segment is annotated as *not aligned* with any English content.

As shown in Table 7, we present several representative samples from our fingerspelling annotation process. Each example includes the full sentence containing a fingerspelled segment, the transcribed character sequence, and the corresponding aligned English word or phrase when available. This protocol ensures that each FS annotation is temporally precise, linguistically grounded, and aligned with surrounding sentence context where possible, enabling reliable training of FS recognition and translation models.

#### C.4 FINAL DATASET STORAGE

The finalized BANZ-FS dataset, curated and annotated by sign language experts and trained annotators, is structured into three task-specific subfolders and is hosted on a public cloud repository. The organization of the dataset is illustrated in Figure 7. Each subfolder corresponds to a specific task: *Fingerspelling Recognition, Fingerspelling Detection*, and *Sign Language Translation*, respectively.

Within each task folder, the dataset is further divided into two main components. The *Annotation* subfolder contains three files: Train, Val, and Test, each storing task-specific labels such as sentence-level alignments, fingerspelling boundaries, or character sequences depending on the task. These annotations are derived from expert manual alignment procedures and reflect high-quality temporal labeling. The *Data* subfolder contains a compressed archive (e.g., Fingerspelling\_Recognition.zip) holding all the corresponding RGB video clips. These videos are already pre-processed to focus on the signer and are trimmed according to the annotated segment durations.

This storage structure ensures modular access for each task, allowing researchers to independently work on detection, recognition, or translation without ambiguity. Additionally, all annotations are time-aligned with video content, facilitating temporal learning and evaluation. An overview of the folder structure is shown in Figure 7, and recommended splits are discussed in Table 2 and Table 6.

# C.5 CONTINUOUS FINGERSPELLING CLIPS

In our annotations, each lexical fingerspelled item is treated as the minimal unit. For example, in the utterance "Here are the forecasts for Brisbane, New South Wales, and Sydney," although the FS segments "BB", "NSW", and "SY" appear consecutively, we annotate each of them as a separate fingerspelling segment with its own time interval. This segmentation strategy results in an average clip length of approximately 1.5 seconds across the dataset.

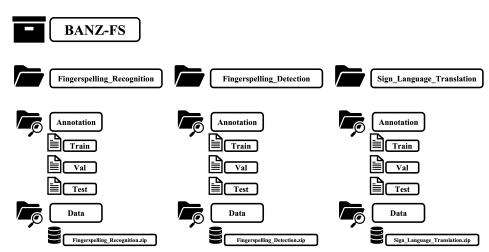


Figure 7: Hierarchical data folders for BANZ-FS on **G** Google Drive.

Table 8: Statistics of isolated versus continuous fingerspelling clips. "Length" refers to total duration in seconds; "Average" is the mean duration per clip.

Source	]	Isolated FS Cli	ips	Continuous FS Clips				
	#Clips	Length	Average	#Clips	Length	Average		
ABC News	22,198	17,483.39	0.79	3,678	6,471.37	1.76		
YouTube	2,149	5,770.38	2.69	374	2,336.38	6.25		
Lab Recordings	10,732	14,141.18	1.31	0	0.00	0.00		

To support research on long-form fingerspelling detection and recognition, we additionally merge temporally adjacent fingerspelling segments and report statistics for these continuous spans. The statistics are summarized in Table 8, and both isolated and continuous segment boundaries will be included in the public release to enable future benchmarking efforts.

These findings highlight the linguistic and stylistic diversity captured in BANZ-FS: fingerspelling in news broadcasts tends to be fast and compressed, whereas YouTube content is slower and more naturalistic. Although our Lab Recordings subset does not include continuous FS clips, it contains fine-grained temporal annotations for each lexical item, enabling generation of high-quality synthetic continuous sequences in future work.

### C.6 DEMOGRAPHIC REPRESENTATION AND COVERAGE

Table 9: Signer Demographic Breakdown by Subset.

Lab Recordings 67 38/29 16–75 BANZ 27/30/10	frican)
N Clina 20 11/10 25.55 Alan 22/6/0	
News Clips 29 11 / 18 25–55 Auslan 23 / 6 / 0	
Web Data 20 7/13 20–45 BSL, NZSL 16/2/2	

As shown in Table 9, we provide a demographic summary of the signers in our dataset, including gender, age range, collection region, and demographics across the three subsets: Lab Recordings, News Clips, and Web Data. While Web and News subsets rely on public sources and offer limited control over signer demographics, we address this by proactively recruiting a diverse signer pool in the Lab Recordings subset, ensuring broader representation in terms of age and racial background. We also confirm that our collection covers participants from multiple regions within Australia, and the Web subset includes samples from the UK and New Zealand. Although Auslan content makes up the majority of the dataset, the BANZSL fingerspelling alphabet is shared across all dialects, providing a solid foundation for cross-dialect generalization. We acknowledge that perfect demographic balance (Section B) is difficult to achieve, but our ongoing efforts in data collection and documentation aim to support transparent and inclusive dataset construction.

1081 1082

1084

1087 1088 1089

1090

1095

1099

1100

1101

1102

1103

1104

1105

1106

1107 1108

1109

1110

1111

1113 1114

1115

111611171118

1119 1120 1121

11221123

1124

1125 1126

1127

1128

1129

1130

1131

1132

1133

# D CONSENT FORM FOR BANZ-FS RECORDING

Due to the inclusion of facial information in our dataset, we obtain consent from volunteers and have them sign the consent form depicted in Figure 8 before recording data. **We do not release personally identifiable information** such as names, ages, occupations, or indications of whether individuals are deaf or hard of hearing. It is important to note that our dataset is strictly for academic use and can not be used for commercial purposes.

# Consent Form for Recording of the Australian Sign Language Dataset Dear Participant, Hello! We are a team dedicated to the research of sign language. We are conducting an academic project aimed at recording and analyzing Australian Sign Language (Auslan). We invite you to participate in this project. The purpose of this project is to facilitate the learning and dissemination of sign language and to enhance understanding and application of Auslan Mode of Participation: You will be recorded while using Auslan for communication. These recordings may include your facial expressions Privacy and Data Use: We commit to using the recorded data solely for academic research purposes and not for any commercial use. All data will be anonymized to ensure the security of your personal information. The video material may be presented at academic conferences, in research papers, or educational courses. Consent Details: 1. I have read and understood the information about the research described above. 2. I agree to participate in the video recordings of Australian Sign Language 3. I understand that my participation is voluntary, and I can withdraw at any time without any adverse consequences 4. I agree that my facial expressions and hand gestures may be recorded and used for academic research Please fill out the following information and sign below to indicate your consent to participate: Email: Signature: Date: We greatly appreciate your participation and support Should you have any questions or require further information, please contact us at: Contact Person: [Name of Coordinator] Email: [Coordinator's Email] Phone: [Coordinator's Phone]

Figure 8: Consent Form for Recording.

# E More Details for Video Representation

**RGB-based:** We use the pre-trained I3D model form (Li et al., 2020a) and features with a window width of 16 and a stride of 2 are extracted:

$$f_t = I3D(F_{t-\frac{n}{2}} \oplus \dots \oplus F_t \oplus \dots \oplus F_{t+\frac{n}{2}}), \tag{1}$$

where  $f_t$  is the representation of the t-th frame, n is the window width, and  $\oplus$  denotes the concatenation operation.

**Pose-based:** Leveraging pose information in action recognition presents significant benefits regarding robustness and semantic representation. We flatten the pose array  $A \in R^{T \times N \times 2}$  to  $A_f \in R^{T \times 2N}$ , where T is the number of frames and N is the number of keypoints. Meanwhile, our experiment results show that using partial body and two hands keypoints will perform better for the sign language translation task.

Table 10: Translation results of Single/Multi-Person SLT gloss-free models on Auslan-Daily News (Shen et al., 2023) and our newly extend Auslan-Daily News V2.

		Ausla	n-Daily Ne	ws V1 (Sh	en et al., 2	2023)	l	Auslan	-Daily New	vs V2	
Single-Per. SLT	Input	R	В1	B2	В3	B4	R	В1	B2	В3	В4
SL-Luong (Luong et al., 2015)	Pose	20.65	19.84	7.81	4.59	2.81	21.71	21.42	10.55	6.58	4.94
SL-Luong (Luong et al., 2015)	RGB	16.14	16.92	7.44	4.07	2.68	15.47	16.43	7.61	5.19	3.91
SL-Transf (Camgöz et al., 2020)	Pose	20.25	21.25	6.57	3.32	2.11	22.17	21.61	8.12	4.84	3.65
SL-Transf (Camgöz et al., 2020)	RGB	14.93	17.64	7.41	3.98	2.52	13.83	13.93	7.02	4.33	3.05
TSPNet-Joint (Li et al., 2020b)	RGB	19.71	18.23	5.97	3.21	2.26	20.09	20.39	7.66	4.23	2.83
MMTLB (Chen et al., 2022a)	RGB	18.90	19.64	5.30	3.26	2.31	16.80	18.80	8.01	5.15	3.68
GASLT (Yin et al., 2023)	Pose	18.76	15.57	6.06	3.72	2.72	24.78	21.43	9.91	6.19	4.26
GASLT (Yin et al., 2023)	RGB	22.01	19.54	7.45	4.41	2.56	23.94	20.99	8.22	6.08	3.77
GFSLT-VLP (Yin et al., 2023)	RGB	27.32	23.00	9.93	6.08	4.43	26.24	22.59	11.50	7.29	5.44
Multi-Per. SLT	Input	R	B1	B2	В3	B4	R	B1	B2	В3	B4
SL-Luong (Luong et al., 2015)	RGB	14.04	15.53	6.11	3.27	2.05	13.61	14.14	6.62	4.67	3.30
SL-Transf (Camgöz et al., 2020)	RGB	13.68	16.58	5.86	2.72	1.55	15.05	17.29	7.63	4.49	3.09
TSPNet-Joint (Li et al., 2020b)	RGB	14.64	17.33	3.86	1.66	1.89	14.68	17.77	6.90	3.69	2.33
MMTLB (Chen et al., 2022a)	RGB	17.76	16.02	4.81	2.83	1.83	20.69	21.21	7.07	3.67	2.43
GASLT (Yin et al., 2023)	RGB	19.73	16.99	6.25	3.44	2.26	20.78	19.43	6.91	4.79	3.56
GFSLT-VLP (Yin et al., 2023)	RGB	20.83	18.93	6.02	4.33	3.05	21.87	18.07	7.66	5.12	4.10

# F EXPERIMENTAL SETTINGS

We mention that all models used in this work are publicly available. Each of the models we use is linked below:

# • Isloated Fingerspelling Recognition:

SL-Transformer (Camgöz et al., 2020) **Q**, Iterative-Att (Shi et al., 2019) **Q**, MiCT-RANet (Mahoudeau, 2020) **Q**, TS-FS-Reg (Chen et al., 2022c) **Q** and FS-PoseNet (Fayyazsanavi et al., 2024) **Q**.

# • Fingerspelling Detection:

Bi-LSTM CTC (Huang et al., 2015) **(C)**, Modified R-C3D (Xu et al., 2017) **(C)**, TS-FS-Det (Chen et al., 2022c) **(C)**, MT-FS-Det (Shi et al., 2021) **(C)**, and SL-Seg (Moryossef et al., 2023) **(C)**.

# • Fingerspelling Recognition in Context and Sign Language Translation:

SL-Luong (Luong et al., 2015)  $\bigcirc$ , SL-Transf (Camgöz et al., 2020)  $\bigcirc$ , TSPNet (Li et al., 2020b)  $\bigcirc$ , MMTLB (Chen et al., 2022a)  $\bigcirc$ , GASLT (Yin et al., 2023)  $\bigcirc$ , and GFSLT-VLP (Zhou et al., 2023)  $\bigcirc$ .

We express profound gratitude to the aforementioned authors for their invaluable contributions.

All the training and fine-tuning experiments are run on a machine with four NVIDIA GeForce RTX 3090 GPUs. We use the default hyperparameters for training the models of fingerspelling-related tasks and sign language translation.

# G THE BASELINE OF AUSLAN-DAILY NEWS V2

To evaluate the effectiveness of existing sign language translation (SLT) models on our extended dataset, we benchmark several state-of-the-art gloss-free SLT systems on both Auslan-Daily News V1 (Shen et al., 2023) and our newly constructed Auslan-Daily News V2. We consider two settings based on input pre-processing:

- Single-Person SLT: The signer is automatically detected and cropped from the original video. This setting eliminates most background noise and visually isolates the signing individual.
- **Multi-Person SLT:** The entire video frame is preserved, including other people and background elements. Although only one person performs sign language in these clips, the presence of scene context and distractors makes translation more challenging.

We evaluate models using RGB and pose input modalities, reporting BLEU scores (B1–B4) and ROUGE (R) metrics in Table 10. The results clearly show that Auslan-Daily News V2 is more

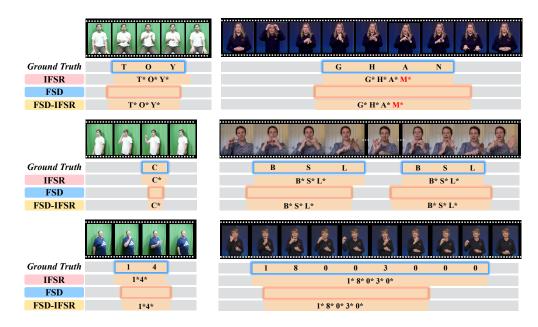


Figure 9: Case study comparing IFSR, FSD, and FSD-R on fingerspelling sequences.

challenging than V1, with slightly lower scores across all models and metrics, especially under the Multi-Person setting. This highlights the increased variability and complexity introduced by our new annotations and broader content coverage.

Among the tested models, GFSLT-VLP (Zhou et al., 2023) consistently achieves the best performance across both datasets and settings, demonstrating the benefit of vision-language pretraining. Notably, Single-Person setups tend to outperform Multi-Person ones, confirming that signer isolation reduces visual ambiguity and aids translation. These baselines provide strong references for future research on realistic, scalable, and context-aware SLT in broadcast news environments.

# H CASE STUDY FOR BANZ-FS FINGERSPELLING DETECTION AND RECOGNITION

Figure 9 illustrates qualitative examples from our BANZ-FS dataset, comparing ground truth annotations with predictions from three systems. Across most examples, FSD-IFSR demonstrates accurate segmentation and character-level recognition, closely matching the ground truth, especially in clear and isolated contexts. However, recognition becomes more challenging in broadcast news settings, as shown in the top-right example. The model confuses the final "N" with "M", likely due to their similar handshapes and coarticulation under fast signing. This highlights the visual ambiguity of adjacent characters in rapid sequences. Another common error arises from temporal proximity of repeated letters. In the bottom-right example, the system fails to distinguish the two or three "0"s near the end, merging them into a single instance. This suggests the need for improved temporal modeling to separate closely spaced, visually similar gestures.

# I CASE STUDY FOR AUSLAN-DAILY NEWS SIGN LANGUAGE TRANSLATION

Table 11 showcases qualitative examples from our Auslan-Daily News V2 translation benchmark. We compare ground-truth sentences with outputs from SL-Luong + Pose (Camgöz et al., 2020) and GFSLT-VLP (Zhou et al., 2023) models. Both models perform well on short, common sentences, but longer or more complex utterances reveal clear differences. GFSLT-VLP captures more complete sentence structures and preserves key semantic information better than the baseline.

Table 11: Case study. We highlight exactly correct translations in red and missing contents in blue.

GT SL-Luong + Pose (Camgöz et al., 2020) GFSLT-VLP (Zhou et al., 2023)	hello and welcome to abc news . hello and welcome to abc news . hello and welcome to abc news .
GT SL-Luong + Pose (Camgöz et al., 2020) GFSLT-VLP (Zhou et al., 2023)	do you think thing have significantly change in the last year. do you think there be escalate do you think thing have significantly change in the last year.
GT SL-Luong + Pose (Camgöz et al., 2020) GFSLT-VLP (Zhou et al., 2023)	to new south wale and the act rain and cool in the northeast . rain and cool in the east . to new south wale and the act rain and cool in the northeast .
GT SL-Luong + Pose (Camgöz et al., 2020) GFSLT-VLP (Zhou et al., 2023)	the prime minister have reject suggestion he redefine his prime minister have a new suggestion the prime minister have reject suggestion that he

# J LLM USAGE STATEMENT

Large Language Models (LLMs) such as ChatGPT are used as general-purpose tools to improve readability and clarity of the manuscript, e.g., for grammar checking, LaTeX formatting, and restructuring sentences. No parts of the research idea, dataset design, or experimental results are generated or influenced by LLMs. All technical contributions and conclusions are solely those of the authors.