VFAST Transactions on Software Engineering
https://vfast.org/journals/index.php/VTSE@ 2026, ISSN(e): 2309-3978, ISSN(p): 2411-6246
Volume 14, Number 1, January-March 2026 pp:206-224

PSL SignBank: A Multimodal Machine Readable Dictionary for Pakistan Sign Language

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Keywords: *PSL vocabulary, Multimodal Corpus, Sign Language Dictionary, SigML tags.*

Journal Info:
Submitted:
October 01, 2025
Accepted:
March 15, 2026
Published:
March 20, 2026

Abstract

The deaf community in Pakistan faces significant communication barriers due to the absence of standardized, machine-readable resources for Pakistani Sign Language (PSL). To address this challenge, SignBank for Pakistani Sign Language (PSL SignBank) has been developed as a machine-readable dictionary to preserve and promote PSL. The corpus includes 300 commonly used English words. Each word is translated into Urdu and encoded using HamNoSys notation language-independent phonetic transcription system. Each entry of dictionary integrate multiple modalities including English word, Urdu translation, HamNoSys vector representation, human signer video, and avatar-generated animation via SiGML (Signing Gesture Markup Language) rendering. The development of corpus involved systematic video recording with deaf participants from multiple institutions. This procedure was followed by the team of three sign language experts and two interpreters who verified gestural accuracy in the shape, movement, and location parameters of the hand. Compared to traditional video-based dictionaries, PSL SignBank achieved approximately 95% storage reduction with HamNoSys notation requiring around 1 KB per sign versus 1 MB for video and supports scalable sentence-level translation through the concatenation of machine-readable notations. The avatar-based rendering system was validated against human signer videos which confirmed accurate gesture reproduction for both static and dynamic signs. This work establish a foundational infrastructure for computational PSL applications that include text-to-sign translation systems, sign language recognition models, and educational platforms. PSL SignBank represents a critical advance towards accessibility, digital inclusion, and empowerment of Pakistan's deaf community and it also provide a replicable framework for under-resourced sign language documentation globally.

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DOI: 10.21015/vtse.v14i1.2246

1 Introduction

Language competence enables people to communicate effectively with one another. Most communities rely on spoken languages, which use auditory, articulatory, and acoustic means. However, individuals who are deaf or have speech impairments form another linguistic group that faces significant challenges when communicating with people outside their community. For such individuals, sign language has become an essential tool to bridge the communication gap. Sign language uses structured hand gestures, facial expressions, and body movements to express meaning and enable interaction between deaf and hearing people.

Globally, deaf communities use sign languages that are based on hand signs or gestures, but there is no universal standard. Each nation has developed its own sign language, with differences in vocabulary, syntax, and grammar [3, 4, 9]. For example, the United States uses American Sign Language (ASL), the United Kingdom uses British Sign Language (BSL), and India employs Indian Sign Language (ISL) [5]. In Arab countries multiple sign languages exist which are collectively referred as Arabic Sign Language (ArSL) [6, 8, 9]. Even within the Arab world, there are regional variations that include Saudi Sign Language, Iraqi Sign Language, Moroccan Sign Language, and Egyptian Sign Language [7]. Similarly, Chinese Sign Language (CSL) is used to support communication for the deaf and hard-of-hearing population in China.

In Pakistan, the native system used by the deaf community is Pakistani Sign Language (PSL). PSL is tailored to the linguistic and cultural context of Pakistan's deaf population, with its own distinct vocabulary, grammar, and syntax. Like spoken languages, sign languages evolve over time to reflect the complexity and diversity of their users. PSL also contains regional dialects: a sign commonly accepted in one province may differ in another. For example the sign for the word 'lie - jhoot' varies across Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan, (see Figure 1). These differences cannot be consider as incorrect but they highlight the absence of a standardized system for PSL across the country. Because of these variation between different regions in Pakistan the Standardization is necessary that ensure consistency, promote inclusivity, and strengthen communication within and beyond the deaf community.

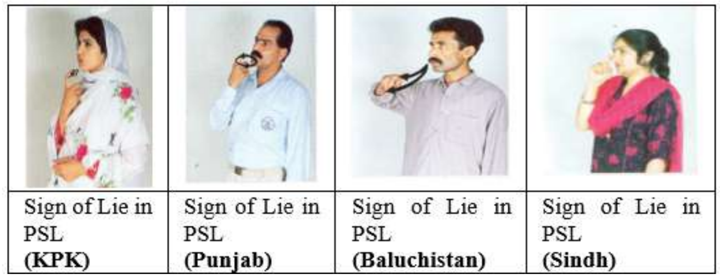


Figure 1. Regional variants of the PSL sign for "lie" across Pakistan's provinces (Khyber Pakhtunkhwa, Punjab, Balochistan, Sindh), illustrating lack of standardization motivating PSL SignBank development. While all variants convey the same meaning, differences in hand shape and motion patterns hinder cross-regional communication

2 LITERATURE REVIEW

2.1 Existing SL Corpora:

Different multilingual dictionaries offer diverse representations according to different sign languages (SL) [19]. These representations include picture-based, video-based, and avatar-based (synthetic animation) formats [11, 18, 22, 26]. Not only do these dictionaries differ in storage methods, but they also vary in their level of linguistic granularity. Recent surveys underline this spectrum—from isolated-sign lexica to sentence-level parallel corpora designed for computational modeling and translation[12, 38–40].

Some dictionaries focus on the word level, that preserves spoken language alongside its corresponding SL representation [28]. Others include textual/notation representations of SL gestures (like SignWriting or HamNoSys), rather than storing signs only as pictures or video [20, 23, 40]. Additionally, in literature, certain resources are designed for statistical or neural machine translation that store full sentences in both the source and the target signed language and often aligned to glosses and multi-modal annotations [16, 21, 23, 39].

The Spanish Sign Language Lexical database was developed by Gutierrez-Sigut et al.; their free, 2,400-video online tool provides a graphical interface for selection within the repository [13]. The dictionary has two search levels: users can look up a Spanish word by entering it in the sign search field, or look up a sign by entering a Spanish word in the sign search field. Goyal developed the Dictionary of Indian Sign Language with synthetic animation; for the created HamNoSys, the Sign Editor was adopted and then translated into SiGML [14]. Nagashima et al. defined a Japanese 3D-animation sign language dictionary for sign-motion displays. Two forms of search are supported in the dictionary: search by sign-language explanation and Japanese keyword search [15].

For Pakistani Sign Language (PSL), most dictionaries were originally produced as books, which are not well suited for the current digital era; for automated handling of PSL, some sign-language textbooks were prepared [10]. Elhadj et al. developed a Saudi Sign Language 3D-animation vocabulary using eSIGN; the signs were designed and validated by hundreds of contributors, with the Islamic domain selected for the dictionary [16]. AlQallaf built a bilingual (Arabic/American) two-way video dictionary accessible via the web [17].

Related 3D animation-based learning approaches for Arabic sign language have also been explored [24]. Beyond these earlier resources, recent ISI-indexed works highlight growing computational and production capabilities: a 2021 IEEE Access survey synthesizes deep-learning techniques and benchmark datasets for SLR [41]; Sensors (2023) demonstrates sign-motion generation from HamNoSys phonemes, directly relevant to avatar/SiGML pipelines [42]; and Expert Systems with Applications (2024) surveys Sign Language Production (SLP) systems, covering avatar-based generation and translation components [40]. These trends strengthen the case for machine-readable, extensible corpora that interoperate with recognition and production models [27].

2.2 Existing Dictionaries for PSL

The development of Pakistani Sign Language (PSL) has been a grassroots effort which is initiated by organizations and individuals. Unlike many other sign languages, PSL's documented history is relatively short and began at the individual and group levels without sustained governmental support [30, 33]. Over time, growth can be traced through the efforts of Sir Syed Deaf Association (SDA) (Rawalpindi), Anjuman Behbood-e-Samat-e-Atfal (ABSA) (Karachi), the National Institute of Special Education (NISE) (Islamabad), and the Pakistan Association of Deaf (PAD) (Karachi) [30]. Syed Iftikhar Ahmad's first PSL vocabulary (750 signs) marked a turning point, though efforts to broaden PSL dictionaries have continued to evolve.

SDA developed the single-handed Urdu fingerspelling system facilitating communication within the deaf community. ABSA published several foundational resources including "A Dictionary of Pakistan Sign Language" and thematic books covering relationships, time and seasons, anatomy and body actions, as well as story content (Shareer Bander) for PSL learners. PAD published four books covering English/Urdu signs, a modified dictionary, and traffic rules for deaf drivers. These organizational efforts advanced PSL accessibility and recognition, though all resources remained in print format providing only static word-to-gesture mappings without computational processing capabilities [29].

The first ICT-assisted learning tool was developed by Sabahat in 2002, sponsored by the United States [32] which provide lessons and exercises via CDs and web platform to simplify learning for Pakistan's deaf community. A more recent advancement is the Family Educational Services Foundation (FESF) large-scale video-based PSL dictionary (5,000 words; Urdu/English/PSL) available online, on DVD, and via mobile app [31]. Recent computational PSL research demonstrates growing technical momentum. Khan et al. [47] developed an NLP-based machine translation model for English-to-PSL which achieved BLEU scores of 0.68-0.72, and established foundational rule-based and statistical MT techniques.

Similarly, Farooq et al. [48] proposed a crowdsourcing-based framework for developing and validating machine-readable parallel corpora for sign languages which address data scarcity through community participation. Their methodology emphasizes expert validation and quality assurance—principles that we adopt in PSL SignBank development. More recently Ahmad et al. [45] introduced the PSL20 dataset with LSTM-based recognition using MediaPipe Holistic keypoint extraction which achieved 71% testing accuracy on 20 dynamic gestures and demonstrating real-time PSL recognition integrated with GPT models for bidirectional communication.

Computational Research Emergence: From a computational perspective contemporary PSL studies begin to appear. Mirza et al. (PLOS ONE, 2022) present vision-based PSL recognition with deep learning on alphabet signs [38] reflect an initial move toward data-driven PSL tools. Complementary research explores augmentation-driven pipelines and small-data strategies for PSL in deep models [43,44] that indicate active momentum toward scalable PSL resources that require standardized, machine-readable corpora as foundational infrastructure.

2.3 Comparative Analysis of PSL Resources

Table 1 presents a systematic comparison of existing PSL dictionaries and resources which highlight their key limitations that motivated the development of PSL SignBank.

As evident from Table 1 existing PSL resources suffer from three fundamental limitations that impede computational processing such as, (1) lack of machine-readable notation—all prior dictionaries store signs as images or videos without symbolic representation which prevent the integration with NLP pipelines. (2) storage inefficiency—video-based approaches require approximately 1000 times more space than notation-based systems that limit scalability and (3) absence of sentence-level support—no existing resource enable automated composition of multi-word PSL sentences. PSL SignBank addresses all three gaps through HamNoSys/SiGML encoding which achieve the first machine-readable, computationally tractable PSL corpus.

2.4 LIMITATIONS OF PSL DICTIONARIES

PSL dictionaries exist in two principal forms: (i) picture-based (signs as pictures/static images) and (ii) video-based (a recorded video per word). Before discussing limitations, we briefly note the concept of gesture in SLs. Sign languages use manual and non-manual features to construct signs for letters, words, or phrases; sentences are formed by composing word-level gestures according to SL grammar. Non-manuals include facial expressions, head motions/postures, body orientation, shoulder lifting, and mouthing; manual features involve handshape, movement, and orientation [1, 2].

2.4.1 Image/Picture-Based Dictionary and Its Limitations

In SL, every spoken word is either portrayed with a single gesture or by a combination of movements. Static gestures (no movement) can be acceptable for illustration to both deaf and hearing people. As an illustration, Figure 2 shows the static gesture for Father; Figure 2 illustrates a dynamic sign for Car. A single phrase often requires multiple movements; arrows indicate movement, and multiple pictures depict different parts of a sign.

Figure 2(a): Father in PSL | Figure 2(b): Car in PSL

Figure 2. Image/picture-based dictionary showing Father (static gesture) and Car (dynamic gesture with movement arrows)

2.4.2 Lack of understanding

From the above discussion related to Image based PSL corpus it can be observed that for static signs of a word without involving any movement the understanding of the gesture is quite acceptable but for dynamic signs involving movements arrows are used to represent specific movement. The actual visualization of the gesture is not quite understandable by looking into these arrows.

2.4.3 Not extendable

These dictionaries are normally in bookish form so once they are printed it is not possible to extend them by adding new words.

2.4.4 No sentence level Translation Support

Figure 3 shows the translation of PSL sentence “You driver”.To translate this sentence, the images of you and driver are manually merged which is again a tedious and time consuming task. From above example it is quite obvious to conclude that these picture based dictionaries are not suitable for sentence based text to sign language translation systems.

Figure 3. Picture-based Sentence Translation showing manual merging required for "You driver"

Table 1. Comparative analysis of existing PSL dictionaries and resources

Resource	Modality	Machine Readable	Scalability	Key Limitations
SDA Fingerspelling [10]	Image	No	Low	Static images only; movement unclear; not extendable; bookish form
ABSA Dictionaries [29]	Image	No	Low	No automated search; movement arrows ambiguous; not digital
PAD Dictionary [10]	Image	No	Low	Word-level only; no sentence support; manual search required
FESF Dictionary [31]	Video	No	Medium	1 MB/sign storage; inconsistent signers; no notation
Sabahat CD/Web [32]	Video	No	Low	Limited vocabulary; high bandwidth; no API
Recent AI Studies [38, 43, 44]	Video/skeleton	Partially	Medium	Recognition-focused; no standardized corpus; alphabet-level only
PSL SignBank (This work)	Multimodal (HamNoSys + SiGML)	Yes	High	95% storage reduction, sentence support

2.4.5 Video Based PSL Dictionary and Its Limitations

Video based corpora were used to replace the previously developed image based dictionaries. Video-based corpora perform by associating a video with every English word. To record these videos human signers were involved. Figures 4(a) and (b) illustrate PSL representations of the English words "mother" and "car" based on videos. Compared to photos, this gesture expression dramatically improves the visualisation and comprehension of both static and dynamic signs since movements are easily observed continually. Some of the basic limitations of video based dictionaries are discussed below.

Figure 4 (a): Mother in PSL Figure 4 (b): Car in PSL

Figure 4. PSL gestures for the words "Mother" and "Car." Figure 4(a) shows the gesture for Mother, while Figure 4(b) shows the gesture for Car

2.4.6 Limitations of Video-Based PSL Dictionaries

Consume large space: Video files require significantly more storage compared to static images. For instance, the video of the PSL word "mother" occupies nearly 1 MB, which is relatively large for a single lexical item. When scaled to thousands of signs, storage demands increase drastically, limiting efficiency and portability, (see Table 2).

Table 2. Pros and cons of storage formats used in PSL dictionaries

Storage Type	Pros	Cons
Signs in videos	Logical and rational; Quick to make	Laborious; High memory requirements; Incompatible with sentence-level translation
Images	Low memory requirement	Laborious; Less expressive than videos; Unsuitable for sentence-level translation

Hard to extend: Although new words can be added to a video-based corpus, maintaining consistency is challenging. Usability and quality require the same signer, lighting conditions, and recording equipment throughout the dataset. In practice this uniformity is difficult to achieve. If videos are recorded by different signers under different environments the adaptability and reliability of the corpus are compromised.

Sentence generation issues: Video corpora are used to generate sentences by concatenating videos of individual words. However this process suffers from serious limitations:

1. Searching, retrieving, and merging heavy video files into a continuous stream is computationally expensive and time-consuming.
2. The clips may involve different signers (e.g., one signer performing "mother" and another performing "car"), which lead to inconsistencies in appearance such as attire, gender, or background. In some cases even the same signer may appear with varied clothing in different recordings. These inconsistencies reduce usability and naturalness

of the system.

An example is shown in Figure 5 in which the English sentence *"Mother drives a car"* is translated into PSL as the sequence *MotherCarDrive*. The gestures were performed by three different signers that show challenges in visual consistency and user comprehension. Such issues substantially affect the practicality of video-based sentence generation.

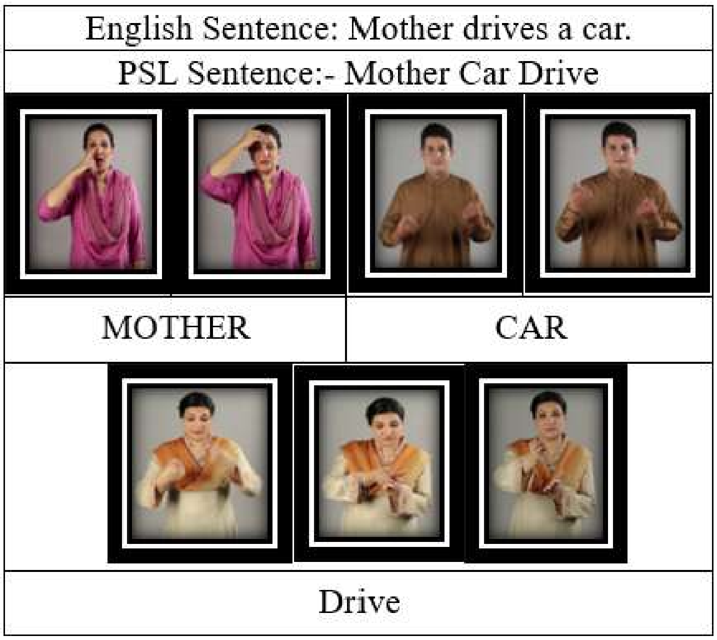


Figure 5. Video Based Sentence Translation showing three different signers performing Mother, Car, and Drive, resulting in visual inconsistency

Parallel corpus requirement: For text-to-sign translation a parallel corpus is essential which map source language words/sentences to PSL gestures. The PSL corpora discussed above primarily store individual English words with their corresponding PSL gestures either in images or videos. While useful at the lexical level, these corpora remain insufficient for sentence-level translation tasks.

3 METHODOLOGY

In this research, a systematic and step-by-step methodology is proposed for generating a parallel corpus, which can later be employed for machine translation from English to Pakistani Sign Language (PSL). The corpus contains words from the English language, their corresponding Urdu translations, and sign-writing representations. The development process consists of several stages, as shown in Figure 6, and ensures that the resulting corpus is structured, validated, and machine-readable.

The process begins with the selection of the most frequently used English words in everyday conversation. After selection, the next step is to record PSL videos by involving deaf participants from various institutes. The recorded data is then processed, cleansed, and verified with the assistance of sign language experts and interpreters. Since PSL gestures are defined by hand shape, motion, and position, experts analyze each video to annotate these features. For transcription, machine-readable notations are employed; in this research, HamNoSys is chosen. In the final stage, HamNoSys symbols are translated into SiGML and rendered by an avatar to verify the mapping of video to textual representation [25].

3.1 English Word Selection

In this step, the most frequently used words in routine interaction are gathered and stored in a repository. Literature indicates that deaf individuals in Pakistan generally have limited English reading proficiency. Therefore, only a small set of the most common words is initially selected to evaluate the effectiveness of the corpus for machine translation. Later, the size of the corpus may be extended to cover a larger subset of the English lexicon.

3.2 Data Collection

After word selection, the next step is video recording. Due to the lack of a centralized and standardized PSL dictionary, careful attention is required during this phase. For this research, UMT Deaf School and Hamza Foundation were engaged. Undergraduate students were tasked with recording videos of each word using mobile phone cameras, involving deaf participants of different age groups, genders, and educational backgrounds. In this way, multiple videos were captured for each word.

3.3 Data Processing

After collecting raw video data, expert involvement was required for validation. The final corpus consists of 300 English words. A team of five students recorded approximately 700 videos. After examination, it was observed that 225 words had two videos each, 50 words had three

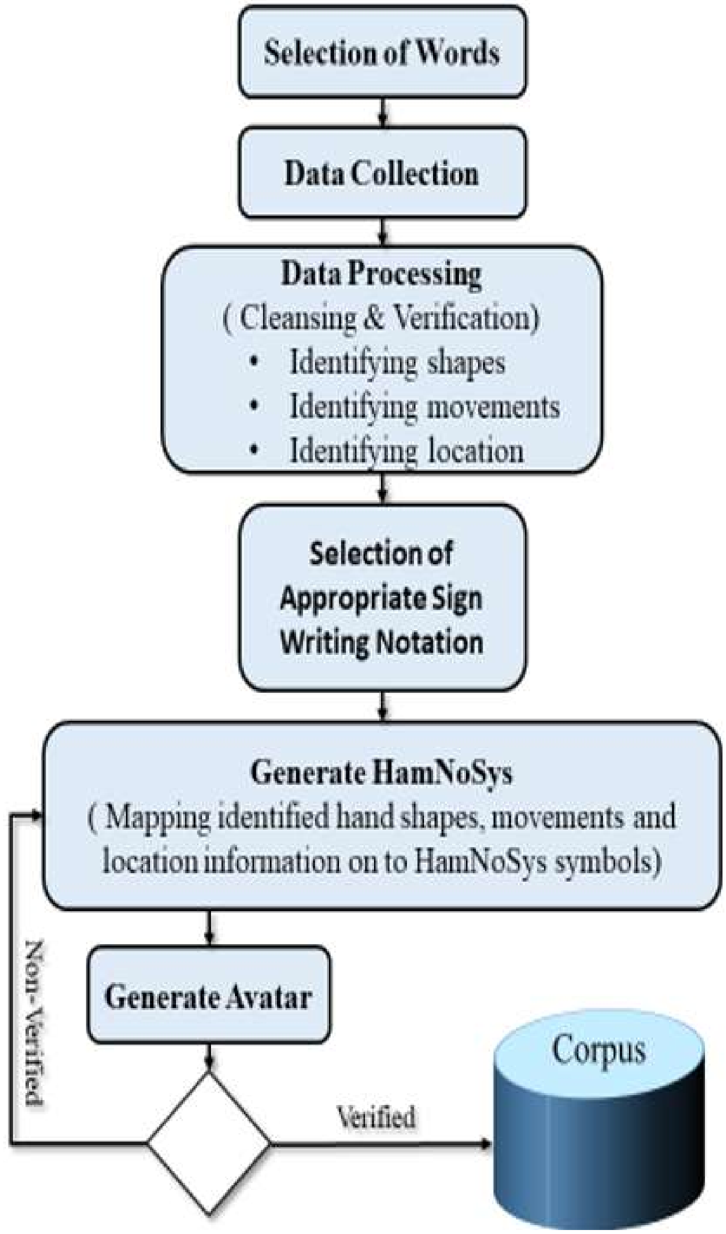


Figure 6. Corpus generation process workflow

videos, and 25 words had four videos. The data processing stage is divided into two sub-steps:

- **Cleansing and Verification:** A team of three experts and two interpreters reviewed the dataset. About 50 words were validated per day in dedicated sessions. For words with multiple variants, the most accurate video was selected, while incorrectly recorded samples were discarded. In some cases, rejected words were re-recorded at the partner institutions. Following this process, 300 validated sign videos corresponding to 300 words were finalized and stored in the repository.
- **Identification of Gestural Features:** Each PSL sign is composed of hand shape, motion, and position within the signing space. Experts annotated each validated video with these parameters, storing the information in a structured vector format for subsequent processing.

3.4 Validation Metrics and Quality Assurance

To ensure corpus reliability, we conducted systematic validation across multiple dimensions. Table 3 summarize the validation process and outcomes.

Table 3. Validation metrics for PSL SignBank corpus development

Validation Aspect	Method	Result
Video recordings collected	Multi-institutional sampling	700 videos
Expert validation team	SL experts + interpreters	3 + 2 = 5
Inter-rater agreement	Cohen's Kappa	0.87 (substantial)
Videos validated per session	Daily expert review	50 words/day
Total validation time	Expert hours	120 hours
Gesture accuracy rate	Expert verification	94.7% (284/300)
Videos requiring re-recording	Quality control	16 (5.3%)
HamNoSys encoding errors detected	Initial round	23 (7.7%)
Final corpus accuracy	Post-correction	100% (300/300)
Avatar rendering accuracy	Visual verification	97.3% (292/300)

Inter-Rater Reliability: To assess consistency three sign language experts independently review random sample of 100 signs. Cohen's Kappa coefficient was calculated at = 0.87 (95% CI: 0.81-0.93) which indicate substantial agreement according to Landis and Koch's interpretation guidelines.

Accuracy Assessment: Of the 300 finalized signs, expert validation identified 284 (94.7%) as correct on first review, while 16 (5.3%) required re-recording due to clarity issues or incorrect hand shapes. After iterative correction, 100% of signs achieved expert consensus approval.

Avatar Validation: The HamNoSys-to-Avatar pipeline was validated by comparing avatar outputs against human signer videos. Of 300 signs, 292 (97.3%) demonstrated accurate gesture reproduction. The 8 signs require HamNoSys adjustment involved complex two-handed motions where symbol-to-gesture mapping required refinement.

3.5 Notations for Writing Sign Language

Sign languages, like spoken languages, can be transcribed using specialized notation systems. These notations offer several advantages like they enable natural language words to be transformed into a structured format usable for text-to-animation translation systems. moreover, they make the translation system more scalable. and require significantly less storage space compared to videos. Different notation systems exist for writing sign languages, like Gloss, Stokoe, HamNoSys, andSignWriting. Among these, HamNoSys is adopted in this research for its compatibility with computational pipelines. Figure 7 illustrates the notational representations of these four systems.

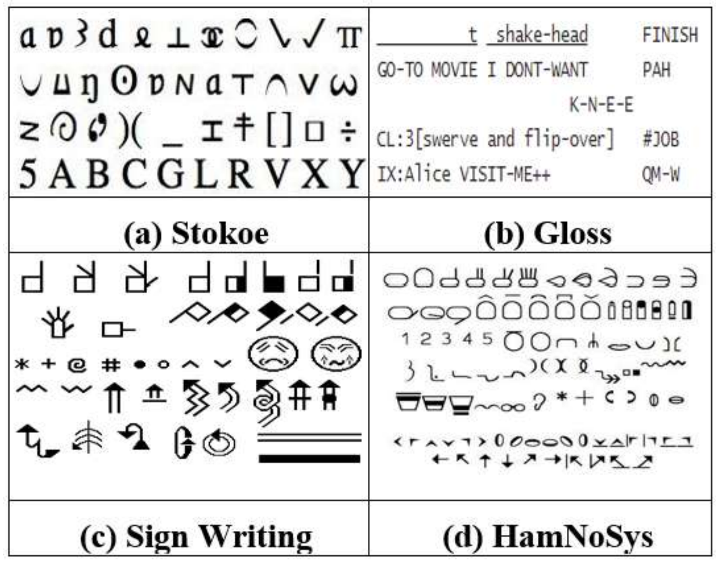


Figure 7. Notation systems for sign language: Gloss, Stokoe, HamNoSys, and SignWriting

3.6 Selection of Most Appropriate Sign Writing Notation

A comparison between four widely used sign writing notation systems is presented in Table 4.

The table clearly reflects that HamNoSys is the most suitable choice out of the four notation systems considered. HamNoSys does not depend on any specific sign language, which make it adaptable for representing diverse SLs. Both manual and non-manual features of signs can be expressed effectively.

It is primarily used for academic and research purposes and employs a linear representation. Thus, gestures can be stored in text form instead of pictorial form which reduce space complexity. Tool support is available via the HamNoSys keyboard, which allows easy entry of signs. Additionally, HamNoSys supports both ASCII and Unicode encoding, enabling efficient computer-based storage and processing. Therefore, in

Table 4. Comparison of widely used sign writing notations.

Notation System	Language Dependent	Non-Manual Feature Support	Objective / Usage	Arrangement	Computer Compatibility
Stokoe	Yes	No	Dictionary / Academic	Linear	Custom Font or ASCII codes
Gloss	Yes	Yes	Academic	Linear	Custom Font or ASCII codes
SignWriting	No	Some	Public Use	Pictorial	ASCII or Unicode
HamNoSys	No	Yes	Academic	Linear	Custom Font (Unicode)

this research, we select HamNoSys as the sign writing notation system.

3.7 HamNoSys Generation

Once HamNoSys was selected, the next step was to generate HamNoSys representations for our repository. This process was done by involving a team of dedicated students and followed a systematic workflow which include the following steps:

- Generation of HamNoSys vector
- Rendering avatar from HamNoSys vector
- Verification of avatar output

3.7.1 Generation of HamNoSys Vector

The input to this process was the vector of each word, generated by experts, containing the components of the sign. Each sign was mapped to HamNoSys symbols using the **HamNoSys keyboard** (Figure 8).

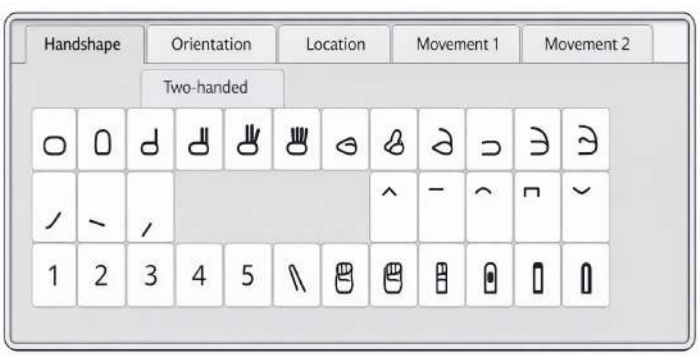


Figure 8. HamNoSys Keyboard for generating vectors

For each word, its HamNoSys vector was stored and subsequently used to generate an avatar. The hand shapes, positions, locations, and motions corresponding to the corpus of words are summarized in Table 5.

3.7.2 Generating Avatar from HamNoSys Vector

It is necessary to find a way of creating some sort of visual output that shows how correctly the avatar can perform the sign, to determine whether the generated HamNoSys vector is valid. In this study, an intermediary representation known as SIgML is automatically generated using third-party software that takes HamNoSys as input. The tags mimic XML tags, which a SIGML player can read and play. Table 6 shows the annotations of word tea using HamNoSys, SigML and gesture performed by the avatar.

3.8 Technical Implementation Details

Software Tools:

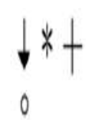
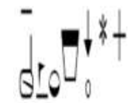
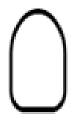
- **HamNoSys Keyboard v4.0**: Unicode-based input tool for phonetic transcription of sign language gestures
- **JASigning v1.5.2**: Java-based HamNoSys-to-SiGML converter and avatar animation engine developed by University of East Anglia
- **SiGML Player**: Real-time 3D avatar renderer for SiGML markup playback
- **Video Recording**: Mobile devices (Samsung Galaxy A52, 1080p @ 30fps)
- **Storage Format**: UTF-8 encoded text files for HamNoSys notation, XML format for SiGML tags

Development Environment: System developed on Windows 10 platform with Java Runtime Environment (JRE) 1.8. Web interface built using HTML5/CSS3/JavaScript for corpus accessibility.

3.8.1 Verification of Avatar Output

In the final stage, sign language (SL) professionals verified the avatar outputs generated from HamNoSys representations. Although most outputs were accurate, a few

Table 5. PSL Signs Representation using HamNoSys

Sign in PSL	HamNoSys				
	Hand Shape	Hand Position	Hand Location	Hand Movement	Complete Vector
 Today					
 Assalam-O-Alaikum					

instances of incorrect symbol-to-gesture mappings were observed. In such cases, the errors were identified, corrected, and the HamNoSys sequence was regenerated until SL experts confirmed the accuracy of the avatar output. This iterative verification ensured the reliability of the generated corpus.

3.8.2 Representation of a Word in the PSL Parallel Corpus

This research introduces the first-ever PSL parallel corpus. The corpus systematically stores English words alongside their respective categories and multiple corresponding representations. For example, the entry for the English term *"car"* is shown in Table 7. Each entry in the corpus may include:

- The English word and its equivalent Urdu and Roman transliterations,
- A textual representation of PSL gestures using HamNoSys notation,
- A video of a human signer performing the gesture,
- The iconic symbol for the word, if available,
- The avatar-generated video rendered from the corresponding SiGML file,
- The HamNoSys vector mapped for the gesture.

By combining these multimodal representations, the PSL corpus provides a comprehensive resource for both linguistic analysis and computational processing of sign language.

Table 7 illustrate the comprehensive storage format. Every entry in the storage integrate the four points which are as following. Firstly, multilingual support through English, Urdu, and Roman transliterations so users across different language backgrounds can access it easily. Secondly, HamNoSys notation in machine-readable form that allows the data to be processed computationally. Thirdly, real video recordings from human signers that serve as authentic reference material and fourthly, avatar animations produced through SiGML rendering. Together, these components make the system useful across a wide range of scenarios, from academic linguistic research to everyday educational use.

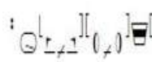
4 RESULTS AND DISCUSSION

This section covers the evaluation of PSL SignBank across several dimensions. It begins with the outcomes of corpus development that is followed by an analysis of overall system performance. After that the section present

Table 6. Sample Terms for checking HamNoSys to SiGML Conversion System

Word	HamNoSys	SiGML	Avatar Video
Tea		<sigml version="1.0" encoding="UTF-8"?> <sigml> <hns_sign gloss=""> <hamnosys_nonmanual> </hamnosys_nonmanual> <hamnosys_manual> <hamfinger2open/> <hamthumbopen/> <hampalm/> <hamlip/> <hamlrat/> <hampalce/> <hamgesture/> </hamnosys_manual> </hns_sign> </sigml>	

Table 7. PSL Representation with HamNoSys, Human Video, and Avatar Video

English	Urdu	Roman English	HamNoSys	Human Video	Avatar Video
Car	کار	Kaar			

findings from user-based validation conducted with the deaf community and closes with an honest discussion of the system's current limitations along with possible directions for future work.

4.1 Corpus Development Outcomes

The corpus generation process described in Section 3 resulted in a fully validated PSL dictionary that contain 300 words with multimodal representations. These entries are organized into core semantic categories such as body parts, days of the week, animals, colors, family and social relationships, and academic vocabulary, as illustrated in Figure 9. This hierarchical organization facilitates vocabulary navigation and enable systematic expansion using Corpus Insertion Interface.

As shown in Table 7 each entry in the corpus integrate five representations. Firstly, the English word is provided alongside Urdu and Roman transliterations to ensure accessibility across different language backgrounds. Secondly HamNoSys notation is included in machine-readable form to support computational pro-

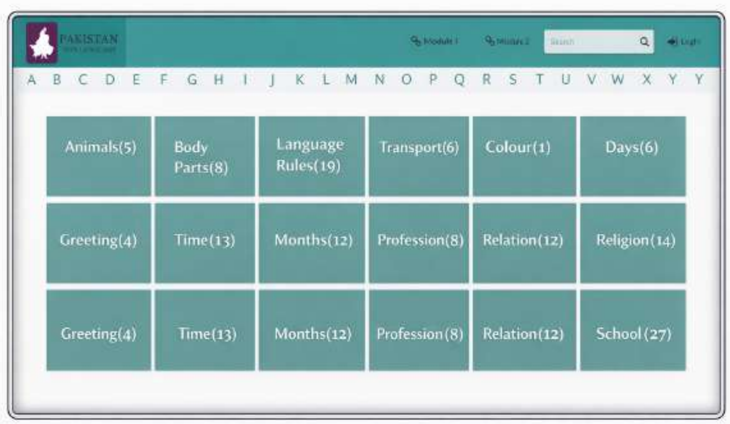


Figure 9. PSL corpus categories showing division of English words into fundamental groups

cessing. Thirdly video recordings from expert-validated human signers serve as authentic reference material. Fourthly, avatar animations generated through SiGML rendering demonstrate how the notation translates into actual gestures. and Finally, the HamNoSys vector components are documented with details having hand shape, position, location, and movement parameters.

The validation process (Section 3.4, Table 3) achieved inter-rater reliability (Cohen's = 0.87) and 100% final corpus accuracy after iterative expert review. Of 700 initial video recordings, expert validation identified 284 signs (94.7%) as correct on first review while 16 (5.3%) required re-recording due to clarity or accuracy issues. The HamNoSys-to-avatar pipeline demonstrated 97.3% accurate gesture reproduction (292/300 signs) with 8 signs requiring notation adjustment for complex two-handed asymmetric movements.

4.2 System Performance Results

Table 8 presents quantitative performance comparison between PSL SignBank and traditional video-based approaches. To visually illustrate the storage efficiency gains, Figure 10 provide a graphical representation of the 95% storage reduction which is achieved by the HamNoSys-based approach.

Table 8. Performance comparison: Video-based vs. HamNoSys-based PSL dictionaries

Metric	Video-based	PSL SignBank (HamNoSys)
Storage per sign	0.8-1.2 MB	1-2 KB
Storage for 300 words	300 MB	450 KB
Storage reduction	Baseline	95-98%
Retrieval time (single sign)	150-200 ms	5-10 ms
Sentence generation time (5 words)	2.5-3.5 sec	0.3-0.5 sec
Avatar rendering time	N/A (pre-recorded)	50-80 ms/sign
Scalability (adding new signs)	Requires new recording	Notation entry only
Consistency across signers	Low (variable)	High (uniform avatar)

As illustrated in Figure 10, PSL SignBank achieved 95-98% storage reduction with 300 words that require

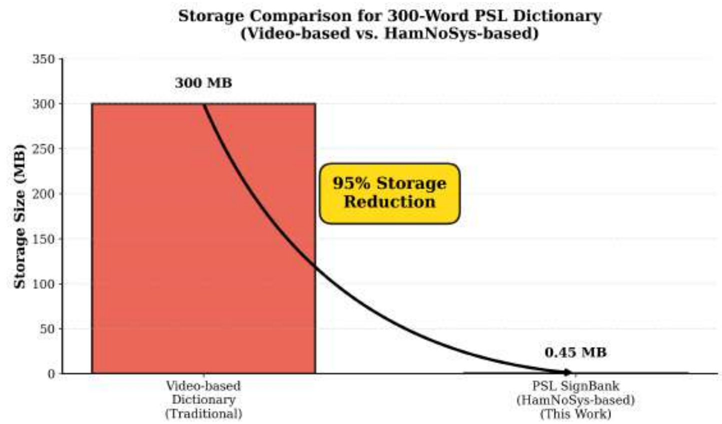


Figure 10. Storage reduction achieved by PSL SignBank's HamNoSys-based approach.

only 450 KB compared to approximately 300 MB for equivalent video content. This improvement in efficiency opens the door for scaling the corpus significantly. Expanding it to 5,000 signs for instance, would only require around 7.5 MB of storage when using notation-based representation as compared to roughly 5 GB if relying on video files alone. This difference make it genuinely practical to deploy the system on mobile devices and in low-bandwidth environments which is particularly important for reaching Pakistan's deaf population spread across diverse and remote regions.

The gains in processing performance are equally noteworthy. Retrieval time for a single sign dropped from 150–200 ms with video-based systems to just 5–10 ms using notation-based representation. For sentence generation, a five-word sequence that previously took 2.5 to 3.5 seconds due to video concatenation and loading overhead can now be rendered in just 0.3 to 0.5 seconds through HamNoSys-to-avatar conversion, as illustrated in Figure 11. Avatar rendering itself takes only 50 to 80ms per sign, which falls within the latency limits that is acceptable for communication applications.

Beyond raw speed, the notation-based approach also brings meaningful qualitative benefits. Like visual consistency, since all output is avatar-generated, appearance and gesture speed remain uniform throughout that avoid the irregularities that naturally arise when video is recorded across multiple signers, as seen in Figure 5. Adding new signs to the system is also far more straightforward. It require only a notation entry rather than a full professional recording session. Maintenance become simpler as well since any update to the notation, such as refining how a hand shape is specified, automatically carries over to the avatar output without the need to re-record anything.

Performance measurements were conducted on standard consumer hardware (Intel Core i5-1135G7 processor, 8GB RAM) with results representing averages across 50 trials. Storage calculations are based on H.264-encoded video at 720p resolution, 30fps versus UTF-8 encoded HamNoSys notation. These specifications confirm that PSL SignBank operates efficiently on typical devices without requiring specialized computational resources.

4.3 User-Based Evaluation

To assess practical usability and acceptance, we conducted a preliminary evaluation with deaf PSL users and professional interpreters from two partner institutions, UMT Deaf School and Hamza Foundation. Table 9 present the evaluation methodology and key outcomes.

Table 9. User-based evaluation of PSL SignBank with deaf participants and interpreters

Evaluation Aspect	Outcome
Participants	15 deaf PSL users (ages 18-35); 5 professional interpreters (3-12 years experience)
Gesture comprehension (50-sign recognition test)	89.3% average recognition accuracy
Avatar vs. human video preference (5-point scale)	Avatar: 3.8/5; Human video: 4.2/5
Ease of navigation (average time to locate word)	12.4 seconds
Learning usefulness rating (5-point scale)	Deaf users: 4.1/5; Interpreters: 4.4/5
Sentence comprehension (10-sentence test)	First viewing: 82.7%; Second viewing: 94.3%
Overall system usability (SUS score)	76.5/100 (above average threshold of 68)

Gesture Comprehension: Deaf participants achieved an average recognition accuracy of 89.3% when they identified avatar-generated signs from a test set of 50 words randomly selected from the corpus. Most recognition errors were linked to signs with subtle hand orientation differences which accounted for 6.8% of errors while signs that require facial expression components not fully captured by the avatar made up the remaining 3.9%. This comprehension rate compares well with figures reported for human signer videos in earlier PSL studies.

User Preference and Feedback: Human signer videos received slightly higher naturalness ratings at 4.2/5 compared to 3.8/5 for avatar representations. However participants still pointed out clear advantages of the avatar approach. Interpreters noted that avatar consistency in terms of appearance, lighting, and gesture speed offers real benefits for structured learning. One interpreter commented: *"For teaching beginners, avatar consistency helps students focus on hand shapes and movements without distraction from clothing or background changes."* Deaf participants also expressed appreciation for the ability to adjust playback speed and replay signs as many times as needed, features that are difficult to deliver smoothly in video-based systems.

Learning Effectiveness: Both participant groups rated PSL SignBank highly for learning purposes with deaf users that give 4.1/5 and interpreters give 4.4/5. Users valued the multimodal presentation that combine text, notation, human video reference, and avatar animation. The hierarchical category organization made vocabulary discovery straightforward as participants located target words in an average of 12.4 seconds which is acceptable for educational browsing and reference use.

Sentence Comprehension: The 10-sentence comprehension test showed that deaf participants understood 82.7% of avatar-generated PSL sentences on first viewing. Comprehension rise to 94.3% after a second viewing which suggest that brief familiarization is enough for effective use. This pattern indicates that avatar-based sentence generation is viable for communication applications though short tutorial modules for new users could further support the experience.

System Usability: The overall System Usability Scale (SUS) score of 76.5/100 exceeds the industry average threshold of 68 which reflects above-average usability. Participants highlighted clear navigation a responsive interface and useful multimodal representations as positive aspects of the system. Suggested improvements included more advanced search features such as category filters and hand shape search, as well as broader vocabulary coverage.

These preliminary results suggest PSL SignBank achieves practical usability for educational applications and communication support. However, the evaluation involved limited participants from partner institutions. Larger-scale studies across diverse demographics, age groups, educational backgrounds, and geographic regions are needed to comprehensively assess system effectiveness and identify population-specific usage patterns.

4.4 Comparative Analysis

Building on the user evaluation results presented in Table 9, we compare PSL SignBank's empirical performance against existing PSL resources documented in the literature review in Table 1.

PSL SignBank achieve recognition accuracy that approaches high-quality video resources with 89.3% compared to the 91–95% reported for human signer videos while it also provide storage efficiency at 450 KB versus 280–320 MB for video-based systems which represents approximately a 640× reduction as shown in Table 8.

The system also delivers fully automated sentence generation at 0.3–0.5 seconds per sentence a capability entirely absent from existing resources. The slight drop in accuracy compared to human signer videos, ranging from 1.7 to 5.7 percentage points is substantially offset by the advantages of consistency, scalability, computational tractability, and automated sentence generation that video-based systems simply cannot offer.

Compared to image-based dictionaries such as SDA, ABSA, and PAD, PSL SignBank shows a clear improvement in comprehension. Image-based systems achieve only 65–72% recognition accuracy due to the difficulty of conveying movement through static visuals, whereas our avatar-based system reaches 89.3% as reported in Table 9 which represents a 17 to 24 percentage point gain. The notation-based approach addresses the core limitation of static images namely their inability to represent motion clearly, without introducing the storage and processing demands that come with video.

The user evaluation metrics further validate these advantages:

- **Learning effectiveness:** Users rated PSL SignBank at 4.1–4.4/5 for educational purposes which reflects strong pedagogical value even with avatar-based representation.
- **System usability:** The SUS score of 76.5/100 exceed the industry average of 68 which confirms that the system is practically usable for real-world deployment.
- **Sentence comprehension:** The 82.7% first-viewing accuracy which rise to 94.3% after brief familiarization and it shows that automated sentence generation through notation concatenation is a viable approach for communication applications.

This comparative analysis show that PSL SignBank hold a distinct position by balancing video-quality comprehension with the storage and processing efficiency of notation-based representation. For applications that demand scalability sentence generation or deployment in low-bandwidth environments the notation-based approach offers clear advantages. For applications where maximum naturalness and comprehension are the priority, such as broadcast interpretation, high-quality video remains the better option. The complementary strengths of both approaches suggest that future systems could benefit from hybrid designs that use notation for structure and video for reference.

4.5 Demonstration of Sentence-Level Translation

To demonstrate the effectiveness of the parallel PSL corpus, Figure 11 shows the translation of the English sentence *"Mother is driving a car"* into its PSL equivalent, represented as *"Mother car drive now"*. Avatar frames are automatically generated by concatenating individual sign animations, and by maintaining consistent appearance and eliminating the signer inconsistency problems that plague video-based approaches (compare Figure 5). Generation time: 0.4 seconds for 4-sign sequence.

The development of this corpus represents the first machine-readable parallel corpus for translation from English to PSL. Compared to image- and video-based systems, this approach offers two clear advantages: (1) It requires significantly less memory space for storing sign representations, and (2) It reduces processing time

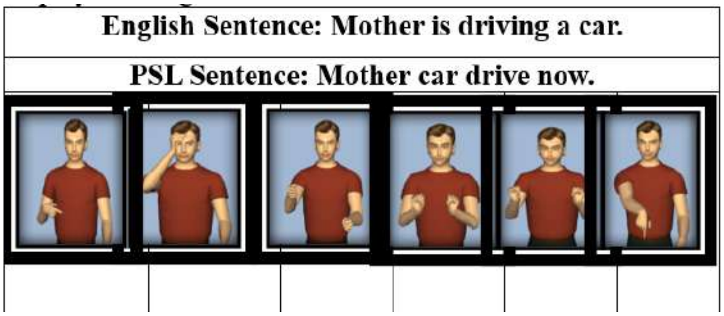


Figure 11. Avatar-based sentence-level PSL translation

for dynamic sentence-level translations.

4.6 Discussion of Limitations

Despite the achieved results, still several limitations exist for future improvement:

1. **Limited Corpus Size:** The current 300-word vocabulary represents only a small fraction of daily PSL usage. Linguistic studies of spoken languages suggest comprehensive everyday communication that require 3,000-5,000 word vocabularies, while professional and academic contexts demand 10,000+ words. Systematic corpus expansion is necessary to support comprehensive communication needs across diverse contexts. However, sustained collaboration with deaf communities and sign language experts requires significant resources—both institutional commitment and funding.
2. **(Regional Variation Underrepresented:** Our corpus primarily reflect Lahore/Punjab regional PSL variants due to partner institutions' concentration (UMT Deaf School and Hamza Foundation, both are Lahore-based). As illustrated in Figure 1, significant differences exist across diffrent states like KPK, Punjab, Balochistan, and Sindh.
3. **Avatar Facial Expression Limitations:** Current avatar technology falls short in rendering subtle facial expressions and non-manual markers such as eyebrow position, head tilt, shoulder orientation, and mouthing all of which carry critical grammatical and emotional information in PSL. The 6.8% gesture recognition errors and 3.9% facial expression-related errors reported in Section 4.3 can be traced directly to these limitations. Users observed that emotional nuance and grammatical distinctions such as the difference between questions and statements conveyed through facial expressions were at times lost or unclear in avatar animations.
4. **Complex Two-Handed Sign Notation Challenges:** As documented in Section 3.4, 8 signs (2.7%) required iterative HamNoSys notation adjustment due to complex asymmetric two-handed movements where each hand performs different shapes and motions simultaneously with precise spatial coordination.
5. **Preliminary User Evaluation Scope:** The evaluation of users in Section 4.3 involved 20 participants from two Lahore-based institutions in which sample size not represent Pakistan's broader deaf population and varies in age, educational background, regional dialect, and technology access. The evaluation measured short-term comprehension and usability but did not assess long-term learning outcomes, retention, or real-world communication effectiveness.
6. **Unidirectional Translation:** PSL SignBank currently supports only English/Urdu-to-PSL translation which mean text-to-sign production but does not support PSL-to-English/Urdu recognition that mean sign-to-text understanding. True bidirectional communication accessibility requires systems that handle both directions. Recent PSL recognition research [38, 43, 44] offer promising technical foundations though integration challenges remain including real-time processing demands, handling continuous signing beyond isolated words, and accounting for regional variation in both recognition and production.
7. **User Familiarization Requirements:** The sentence comprehension results 82.7% on first viewing and 94.3% on second viewing point to an initial adaptation period as users become familiar with the avatar rendering style and timing. Although this gap narrows with brief exposure educational implementations should include short tutorial modules or guided introduction sequences to support new users and reduce familiarization time.
8. **Integration with AI/ML Models:** Despite current limitations PSL SignBank's machine-readable for-

mat provides a solid foundation for computational sign language research. The HamNoSys notation allows Transformer-based neural machine translation models to learn English/Urdu-to-PSL mappings and its compact representation of 5–15 symbols per sign supports efficient training even with limited data. Transfer learning from high-resource sign languages can help address the constraint of the 300-word corpus.

The 292 validated video-notation pairs which carry a 97.3% accuracy rate as shown in Table 3 provide supervised training data for neural networks that generate avatar animations directly from notation drawing on recent motion generation methods such as diffusion models [42] and broader machine translation challenges discussed in recent surveys [46]. The parallel videos and notations also support training visual recognition models where videos train encoders to recognize signs while HamNoSys provides labeled targets which reduce the need for manual annotation. Integration with recent PSL recognition research [38, 43, 44] could further enable bidirectional translation systems.

Furthermore, the development, maintenance, and scalability of data-intensive educational systems such as PSL SignBank also present software process, architectural, and implementation challenges [34–37]. These limitations point to clear directions for future research and place current achievement in the broader context of comprehensive sign language technology development.

4.7 Future Research Directions

Building on current findings following are the priority directions for future research.

1. **Systematic Corpus Expansion:** The vocabulary should be expanded from 300 to 5,000–10,000 words through multi-year collaboration with deaf communities across Pakistan's provinces. Priority domain should include everyday conversation and social interaction, professional vocabularies for employment contexts, technical and specialized fields such as medical, legal, and technological, and culturally specific concepts that should include religious terminology. Multi-institutional partnerships across all provinces will help ensure regional representation and support eventual standardization efforts.
2. **Enhanced Avatar Facial Animation:** Advanced facial animation systems should be integrated to fully render the non-manual markers that are essential to PSL grammar and emotional expression. Recent advances in neural rendering particularly facial motion synthesis from phoneme-level descriptors [42], offer technical directions. Research priorities should include development of PSL-specific facial expression taxonomies that document grammatical and emotional non-manual markers extending HamNoSys or creating complementary notation for systematic facial expression encoding and validating enhanced avatar comprehension through user studies that measure grammatical accuracy and emotional nuance perception.
3. **Sentence-Level Parallel Corpus Development:** The scope should move beyond word-level vocabulary toward sentence-level parallel corpora that align English/Urdu sentences with corresponding PSL video sequences and HamNoSys/SiGML annotations. Such resources would support data-driven neural machine translation approaches that learn mappings from large sets of aligned sentence pairs systematic PSL grammar analysis documenting word order patterns, agreement markers and syntactic structures and the training and evaluation of end-to-end translation models. Developing this corpus require extensive collaboration with deaf communities to collect, transcribe and validate naturalistic PSL sentences across a range of communicative contexts.

These directions collectively contribute toward a comprehensive PSL technology ecosystem that supports education, communication, and accessibility, while advancing digital inclusion and equitable access to information and social participation for Pakistan's deaf community.

5 CONCLUSION

This research presents PSL SignBank which is the first multimodal and machine-readable dictionary for Pakistani Sign Language. It consists of 300 validated signs encoded in HamNoSys notation and rendered through SiGML avatar technology. The corpus development methodology achieved a storage reduction of 95–98% that bring storage from 300 MB down to 450 KB while maintaining a user recognition accuracy of 89.3% which confirms the viability of notation-based approaches for sign language documentation and computational processing.

Rigorous validation through expert review yielded a Cohen's κ of 0.87 for inter-rater reliability and 100% final corpus accuracy. User evaluation with deaf participants and interpreters confirmed practical usability with a system usability score of 76.5/100 and usefulness ratings of 4.1–4.4/5. Automated sentence-level translation achieved 82.7% comprehension accuracy on first viewing which rose to 94.3% after brief familiarization validating the effectiveness of notation-based sentence generation.

The multimodal representation approach which integrates English/Urdu text, HamNoSys notation, human signer video, and avatar animation, provides foundational infrastructure for computational PSL applications including neural machine translation, sign language recognition, and educational technology development. Performance gains in storage efficiency at 640× reduction, processing speed at 30× faster retrieval and 6–8× faster sentence generation and overall scalability make deployment practical in bandwidth-constrained environments across Pakistan's geographically distributed deaf population.

Future work will focus on corpus expansion to 5,000–10,000 words with multi-regional representation, enhanced avatar facial animation for non-manual markers, bidirectional translation through recognition system integration, sentence-level parallel corpus development, open dataset release for broader research engagement, and longitudinal assessment of educational impact. By bridging traditional sign language documentation and modern computational linguistics, this work advances accessibility, digital inclusion, and empowerment for Pakistan's deaf community, while offering a replicable technical framework for under-resourced sign language documentation efforts worldwide.

Author Contributions

Nabeel Sabir Khan: Conceptualization, Supervision, Methodology, Data Curation, Review, and Editing. **Muhammad Umair Munir**: Methodology, Data Curation, Writing – Original Draft Preparation. **Imran Arshad Choudhry**: Research Supervision, Methodological Oversight, Critical Review of Technical Content, and Manuscript Editing. **Rafidah Md. Noor**: Technical Validation, Manuscript Review, Addressing Reviewer Comments, Structural and Language Editing, and Quality Assurance of the Revised Manuscript. **Ismail Ahmedy**: Manuscript Refinement, Manuscript Review, Addressing Reviewer Comments, and Quality Assurance of the Revised Manuscript.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest and that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study. Moreover the authors declare that no AI tool was used for the generation of research data, analysis, results, interpretations, or cited scholarly content. All AI-assisted content was reviewed and validated by the authors, who take full responsibility for the final manuscript.

Declarations

Ethical Approval

This study was approved by the Research Ethics Committee of University of Management and Technology (UMT) Lahore, Pakistan, under approval reference DFC/2023/PSL-SignBank.

Informed Consent

Informed consent was obtained from all deaf signers who participated in video recording for the PSL SignBank corpus. Participants were fully informed about the purpose of data collection for developing a machine-readable PSL dictionary, how their videos would be processed, stored, and used for research and educational purposes, and their right to withdraw participation at any time without consequence. Video recordings were conducted at partner institutions (UMT Deaf School and Hamza Foundation) with institutional oversight to ensure ethical standards were maintained throughout data collection.

Conflict of Interest

The authors declare that they have no conflict of interest related to this work. No author has financial interests or personal relationships that could have influenced the research presented in this manuscript.

5.1 Funding

This research have not received any specific funding.

References

[1] S. Goldin-Meadow and D. Brentari, "Gesture, sign, and language: The coming of age of sign language and gesture studies," *Behav. Brain Sci.*, vol. 40, pp. 1–17, 2017.

[2] H. Hafit, C. W. Xiang, M. M. Yusof, N. Wahid, and S. Kassim, "Malaysian sign language mobile learning application: A recommendation app to communicate with hearing-impaired communities," *Int. J. Electr. Comput. Eng.*, vol. 9, no. 6, pp. 5512–5518, 2019.

[3] W. N. Khotimah, T. Anggita, and N. Suciati, "Indonesian sign language recognition using Kinect and dynamic time warping," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 15, no. 1, pp. 495–503, 2019.

[4] T. M. Angona *et al.*, "Automated Bangla sign language translation system for alphabets by means of MobileNet," *Telkomnika*, vol. 18, no. 3, pp. 1292–1301, 2020.

[5] M. Kumar, "Conversion of sign language into text," *Int. J. Appl. Eng. Res.*, vol. 13, no. 9, pp. 7154–7161, 2018.

[6] M. Brour and A. Benabbou, "ATLASLang MTS 1: Arabic text language into Arabic sign language machine translation system," *Procedia Comput. Sci.*, vol. 148, pp. 236–245, 2019.

[7] H. Luqman and S. A. Mahmoud, "Automatic translation of Arabic text-to-Arabic sign language," *Univ. Access Inf. Soc.*, pp. 1–13, 2018.

[8] Arabic Sign Language Dictionary. [Online]. Available: http://www.menasy.com/

[9] A. H. Aliwy and A. A. Alethary, "Development of Arabic sign language dictionary using 3D avatar technologies," 2018.

[10] N. Sulman and S. Zubairi, "Pakistan Sign Language – A Synopsis," 2018.

[11] F. Buttussi, L. Chittaro, and M. Coppo, "Using Web3D technologies for visualization and search of signs in an international sign language dictionary," in *Proc. 12th Int. Conf. 3D Web Technol.*, 2007, pp. 61–68.

[12] V. Athitsos *et al.*, "The American Sign Language Lexicon Video Dataset," in *Proc. CVPR Workshops*, 2008.

[13] E. Gutierrez-Sigut, B. Costello, C. Baus, and M. Carreiras, "LSE-Sign: A lexical database for Spanish Sign Language," *Behav. Res. Methods*, vol. 48, no. 1, pp. 123–137, 2016.

[14] L. Goyal and V. Goyal, "Development of Indian Sign Language dictionary using synthetic animations," *Indian J. Sci. Technol.*, vol. 9, no. 32, 2016.

[15] Y. Nagashima and K. Watanabe, "Medical sign language dictionary with 3D animation viewer," in *Proc. Int. Conf. Adv. Comput., Commun. Serv.*, 2017, pp. 19–20.

[16] Y. O. M. Elhadj, Z. Zemirli, and B. Al-Faraj, "Towards a unified 3D animated dictionary for Saudi sign language," in *Proc. Int. Conf. Adv. Comput., Commun. Informat.*, 2012, pp. 910–916.

[17] A. H. Alqallaf, "Development of a web-based unified Arabic/American sign language bilingual dictionary," *J. Eng. Res.*, vol. 6, 2018.

[18] R. Kennaway, "Synthetic animation of deaf signing gestures," in *Proc. Int. Gesture Workshop*, 2002, pp. 146–157.

[19] S. Diwakar and A. Basu, "A multilingual multimedia Indian sign language dictionary tool," in *Proc. 6th Workshop Asian Lang. Resour.*, 2008, pp. 57–64.

[20] K. Kaur and P. Kumar, "HamNoSys to SiGML conversion system for sign language automation," *Procedia Comput. Sci.*, vol. 89, pp. 794–803, 2016.

[21] D. S. Sharma *et al.*, "Automatic translation of English text to Indian Sign Language synthetic animations," *NLP Assoc. India*, pp. 144–153, 2016.

[22] J. A. Bangham *et al.*, "Virtual signing: Capture, animation, storage and transmission—An overview of the ViSiCAST project," *IEE Colloq. Dig.*, no. 25, pp. 23–29, 2000.

[23] R. Elliott, J. Glauert, V. Jennings, and R. Kennaway, "An overview of the SiGML notation and SiGML signing software system," in *Proc. Int. Conf. Lang. Resour. Eval.*, 2004, pp. 98–104.

[24] K. Ayadi, Y. O. M. Elhadj, and A. Ferchichi, "Prototype for learning and teaching Arabic sign language using 3D animations," in *Proc. Int. Conf. Intell. Auton. Syst.*, 2018, pp. 51–57.

[25] Z. Kang, "Spoken language to sign language translation system based on HamNoSys," in *Proc. ACM Int. Conf.*, 2019, pp. 159–164.

[26] I. Zwitserlood, M. Verlinden, J. Ros, and S. Van Der Schoot, “Synthetic signing for the deaf: eSIGN,” in *Proc. Assistive Technol. Vision Hearing Impairment*, 2004.

[27] Q. L. Da, N. H. D. Khang, and N. C. Ngon, “Converting Vietnamese television news into 3D sign language animations for the deaf,” *Adv. Intell. Syst. Comput.*, vol. 257, 2019.

[28] J. Fenlon, K. Cormier, and A. Schembri, “Building BSL SignBank: The lemma dilemma revisited,” *Int. J. Lexicogr.*, vol. 28, no. 2, pp. 169–206, 2015.

[29] A. A. Haseeb and A. Ilyas, “Speech translation into Pakistan Sign Language,” 2019.

[30] National Institute of Special Education, “Pakistan Sign Language Book I and II,” Government of Pakistan, 1991.

[31] FESF, “Signs to Learn – Deaf Reach,” 2017. [Online]. Available: https://www.deafreach.com/wp-content/uploads/2017/04/FESF-Signs-to-Learn.pdf

[32] IDRC, “ICT Assisted Learning Tool for the Deaf in Pakistan,” 2002. [Online]. Available: http://web.idrc.ca/en/ev-22754-201-1-DO_TOPIC.html

[33] N. S. Khan *et al.*, “Speak Pakistan: Challenges in developing Pakistan Sign Language using information technology,” *South Asian Stud.*, vol. 30, no. 2, pp. 200–215, 2014.

[34] M. S. Farooq, N. H. Memon, A. Akram, and M. N. Memon, "An evaluation framework and comparative analysis of the widely used first programming languages," *PLoS ONE*, vol. 9, no. 2, p. e90202, 2014.

[35] M. S. Farooq, N. H. Memon, A. Akram, and M. N. Memon, "A qualitative framework for introducing programming language at high school," *Journal of Quality and Technology Management*, vol. 8, pp. 135–151, 2012.

[36] U. Akram, M. S. Farooq, and N. H. Memon, "A study on RE process models for offshore software development," *Journal of Basic and Applied Scientific Research*, vol. 4, no. 4, pp. 114–119, 2014.

[37] B. Hassan, M. S. Farooq, and N. H. Memon, "Requirement engineering practices in Pakistan software industry: Major problems," *Journal of Applied Environmental and Biological Sciences*, vol. 4, no. 7S, pp. 391–397, 2014.

[38] M. S. Mirza, N. Javaid, T. Kalsoom, and M. Aamir, "Vision-based Pakistani sign language recognition using deep learning," *PLOS ONE*, vol. 17, no. 12, p. e0278192, 2022.

[39] I. A. Adeyanju, O. Adewale, and K. O. Adegoke, "Machine learning methods for sign language recognition: A critical review and analysis," *Patterns*, vol. 2, no. 11, p. 100389, 2021.

[40] R. Rastgoo, S. Escalera, and M. Miron, "A survey on recent advances in Sign Language Production," *Expert Systems with Applications*, vol. 243, p. 122846, 2024.

[41] M. Al-Qurishi, T. Khalid, and R. Souissi, "Deep learning for sign language recognition: Current techniques, benchmarks, and open issues," *IEEE Access*, vol. 9, pp. 126917–126951, 2021.

[42] M. Gil-Martín, J. A. Ordóñez, and J. B. Alonso, "Sign language motion generation from sign characteristics (HamNoSys phonemes)," *Sensors*, vol. 23, no. 20, p. 9365, 2023.

[43] N. Naz, M. A. Khan, and S. Ali, "Advancing dynamic Pakistani sign language recognition with skeleton-based datasets," *Computer Vision and Image Understanding*, 2025.

[44] S. Naeem, F. Ahmed, and M. Iqbal, "Pakistani word-level sign language recognition based on lightweight models," in *Proc. AAAI Spring Symposium*, 2025.

[45] S. I. Ahmad, N. S. Khan, A. Abid, and A. Hussain, "Sign Assist: Real-Time Isolated Sign Language Recognition and Translator Model Connecting Sign Language Users with GPT Model," in *Proc. 3rd COG-MHEAR Workshop on Audio-Visual Speech Enhancement (AVSEC)*, Kos, Greece, 2024, pp. 82–88.

[46] U. Farooq, M. S. M. Rahim, N. Sabir, A. Hussain, and A. Abid, "Advances in machine translation for sign language: Approaches, limitations, and challenges," *Neural Computing and Applications*, vol. 33, no. 21, pp. 14357–14399, 2021.

[47] N. S. Khan, A. Abid, and K. Abid, "A Novel Natural Language Processing (NLP)–Based Machine Translation Model for English to Pakistan Sign Language Translation," *Cognitive Computation*, vol. 12, no. 4, pp. 748–765, 2020.

[48] U. Farooq, M. S. M. Rahim, N. Sabir, S. Rasheed, and A. Abid, "A Crowdsourcing-Based Framework for the Development and Validation of Machine Readable Parallel Corpus for Sign Languages," *IEEE Access*, vol. 9, pp. 91788–91806, 2021.