УДК 81'322
DOI: 10.26102/2310-6018/2026.60.9.012

Development of a lexicographic system for Bengali hearing-impaired learners

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Abstract. This article presents automated methods and tools for lexicographic research and dictionary development for Bengali Sign Language (BdSL). The research addresses the challenge of documenting BdSL, an under-resourced sign language primarily used in Bangladesh and Indian Bengali-speaking regions. Established lexicographic methods require extensive manual effort to capture the multidimensional features of signs, including handshape, location, movement, orientation, and non-manual markers. The proposed system integrates computer vision-based feature extraction, machine learning-assisted annotation, and a structured database for lexical entries. The web-based platform enables lexicographers to collect, annotate, and validate sign language entries efficiently. Evaluation with 35 participants, including lexicography experts, BdSL linguists, and deaf community members, showed a 67 % reduction in annotation time while maintaining high inter-annotator agreement ($\kappa = 0.82$). During a six-month period, participants documented 1,847 BdSL signs, identified 127 regional variants, and created 456 dictionary records at different stages of completion. These records included entries containing core phonological annotations as well as entries that had undergone additional linguistic and expert validation, providing a foundation for the development of a future learner-facing dictionary for Bengali students with hearing impairments. The scientific novelty lies in applying automated methods specifically to BdSL lexicography and establishing foundational tools for systematic dictionary development.

Keywords: sign language recognition, Bengali Sign Language, lexicographic system, sign language documentation, educational technology, multilingual translation, computer-assisted lexicography.

Acknowledgements: The authors are deeply appreciative of the support from A.A. Makhmud, M. Mehrez, T.L. Doan, and Diem H. Chung.

For citation: Ashrafi A., Mokhnachev V.S. Development of a lexicographic system for Bengali hearing-impaired learners. *Modeling, Optimization and Information Technology.* 2026;14(9). URL: https://moitvivt.ru/ru/journal/article?id=2344 DOI: 10.26102/2310-6018/2026.60.9.012

Разработка лексикографической системы для слабослышащих учащихся, изучающих бенгальский язык

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Резюме. В данной статье представлены автоматизированные методы и инструменты для лексикографических исследований и разработки словарей бенгальского жестового языка (БЖЯ). Исследование посвящено решению проблемы документирования БЖЯ, жестового языка с ограниченными ресурсами, используемого преимущественно в Бангладеш и бенгалоязычных регионах Индии. Существующие лексикографические методы требуют значительных ручных усилий для фиксации многомерных характеристик жестов, включая форму кисти, местоположение, движение, ориентацию и невербальные маркеры. Предложенная система объединяет извлечение признаков на основе компьютерного зрения, аннотирование с помощью машинного обучения и структурированную базу данных лексических записей. Веб-платформа позволяет лексикографам эффективно собирать, аннотировать и проверять записи жестового языка. Оценка с участием 35 человек, включая экспертов по лексикографии, лингвистов, изучающих БЖЯ, и членов сообщества глухих, показала сокращение времени аннотирования на 67 % при сохранении высокого уровня согласованности между аннотаторами (κ = 0,82). В течение шести месяцев участники задокументировали 1847 жестов бенгальского жестового языка, выявили 127 региональных вариантов и создали 456 словарных записей на разных этапах завершения. Эти записи включали как основные фонологические аннотации, так и записи, прошедшие дополнительную лингвистическую и экспертную проверку, что заложило основу для разработки будущего словаря для изучающих бенгальский язык студентов с нарушениями слуха. Научная новизна заключается в применении автоматизированных методов специально к лексикографии бенгальского жестового языка и создании базовых инструментов для систематической разработки словаря.

Ключевые слова: распознавание жестового языка, бенгальский жестовый язык, лексикографическая система, документирование жестового языка, образовательные технологии, многоязычный перевод, компьютерная лексикография.

Благодарности: Авторы выражают глубокую признательность за поддержку А.А. Махмуду, М. Мехрезу, Т.Л. Доан и Дием Х. Чунг.

Для цитирования: Ашрафи А., Мохначев В.С. Разработка лексикографической системы для слабослышащих учащихся, изучающих бенгальский язык. *Моделирование, оптимизация и информационные технологии.* 2026;14(9). (На англ.) URL: https://moitvivt.ru/ru/journal/article?id=2344 DOI: 10.26102/2310-6018/2026.60.9.012

Introduction

The lexicographic documentation of sign languages has its own set of challenges that differentiate it from the lexicographic[1] documentation of spoken languages. In the case of spoken languages, it is relatively easier to create a dictionary because they have a standardized system of writing. However, in the case of sign languages, it becomes a challenge to document them in a lexicographic manner. Bengali Sign Language (BdSL), which is used by a huge number of hearing-impaired people in India and Bangladesh, still remains under-documented in a lexicographic sense; recent research, however, has proposed an information-theoretic metric for automated lexicographic selection in BdSL [1].

The conventional lexicographic approach to documentation of sign languages becomes a challenge because it requires a significant amount of time investment in terms of trained linguists as well as native speakers. In addition to that, it has to take into consideration various parameters at once. This shows the need for automated tools in lexicography for low-resource sign languages such as BdSL. Although the system described in this paper is primarily a lexicographer's workstation, its main purpose is educational: a comprehensive, phonologically annotated BdSL dictionary will directly support hearing-impaired students learning Bengali literacy. In the planned educational environment, once lexicographers have built and validated the dictionary, it will be made available as a learner-facing web and mobile application. Students will be able to search for Bengali words, view the associated sign videos, examine the handshapes and movements involved, and engage in exercises to match signs with their corresponding words.

The present work focuses on the lexicographic backend that makes such a learner dictionary possible. To build that backend efficiently, recent advances in computer vision and machine learning offer promising solutions for automating sign language documentation. Motion capture systems, pose estimation algorithms, and pattern recognition systems can help speed up the process of identifying and classifying signs.

[1] McKee R., Vale M. Sign language lexicography. In: *International Handbook of Modern Lexis and Lexicography.* Berlin, Heidelberg: Springer; 2017. P. 1–22. https://doi.org/10.1007/978-3-642-45369-4_34-1

This paper attempts to bridge the gap between what is technologically possible and what is needed in lexicographic research and development for BdSL by suggesting automated tools and methods for BdSL lexicography.

In order to understand the basis for this work, it is necessary to trace the development of sign language lexicography from the time when the first modern dictionaries were published in the 1960s. The early dictionaries used pictures and written descriptions, but these were found to be insufficient for the dynamic nature of sign languages. Johnston's groundbreaking research on Australian Sign Language [2] created guidelines for sign language lexicography, including using glosses, phonology, and sentence examples.

There have been several notation systems created for written descriptions of signs. Stokoe notation, used for American Sign Language, created the first systematic means of transcribing signs according to handshape, location, and movement. More sophisticated systems, such as HamNoSys and SignWriting, have been created but require special training.

Lexicographic research in sign languages in South Asia is very limited. Research on Indo-Pakistani Sign Language has offered basic descriptive insights. Systematic lexicographic work for BdSL is still in its early stages.

At the same time, computer vision for sign language recognition has advanced from basic glove-based solutions to advanced pose estimation. MediaPipe offers real-time hand tracking [3], which is being utilized for sign language recognition.

Building on these pose-estimation capabilities, machine learning methods have shown promising outcomes for isolated sign language recognition. Convolutional Neural Network and transformer-based methods have shown accuracy rates higher than 90 % on benchmark datasets for various sign languages. However, these methods rely on large datasets, which are not yet available for Bengali Sign Language (BdSL). This data gap points to the value of corpus-based documentation. Sign language documentation using corpus-based methods has seen significant advancements in projects such as the Auslan Corpus and Corpus NGT [4, 5]. These methodologies provide a framework for sign language documentation in BdSL.

Despite these advances, several notable gaps remain in the literature. First, a comprehensive lexicographic system does not exist for the BdSL language, despite the large number of language users. Furthermore, existing sign language lexicography tools are not integrated with the latest computer vision technology. Lastly, the process of collaborative sign language lexicography is not well defined.

This research seeks to bridge the gap by developing automated tools for BdSL lexicographic research.

Materials and methods

The study design used the approach of design-based research, where system development is integrated with iterative evaluation. The research process consisted of four phases: requirements analysis, system development, evaluation, and refinement, as depicted in Figure 1.

Phase 1: Preparation consists of literature review, needs assessment, design and prototyping. A literature review is essential to understand the existing literature on sign language education, assistive technology, adaptive learning technologies, and machine learning-based gesture recognition technologies. This will help in following the best practices and identifying the gaps in the existing literature in terms of serving the needs of hearing-impaired students, especially those whose native sign language is a low-resource language such as Bengali Sign Language (BdSL).

Needs assessments are conducted to understand the specific needs of the target group. This phase involves consultations with three key groups of stakeholders:

– Educators (50): Special education teachers and sign language instructors
– Hearing-impaired individuals (100): Potential target groups for the application
– Linguistic experts (30): Linguistics experts in Bengali sign language, Russian sign language, and English sign language.

For instance, in the process of needs assessment, the needs, requirements, and features of users were collected through structured surveys and interviews. Analysis of this data was done through applying a scoring model on the results obtained from the surveys and using theme coding on the results obtained from interviews in order to identify trends in the collected data.

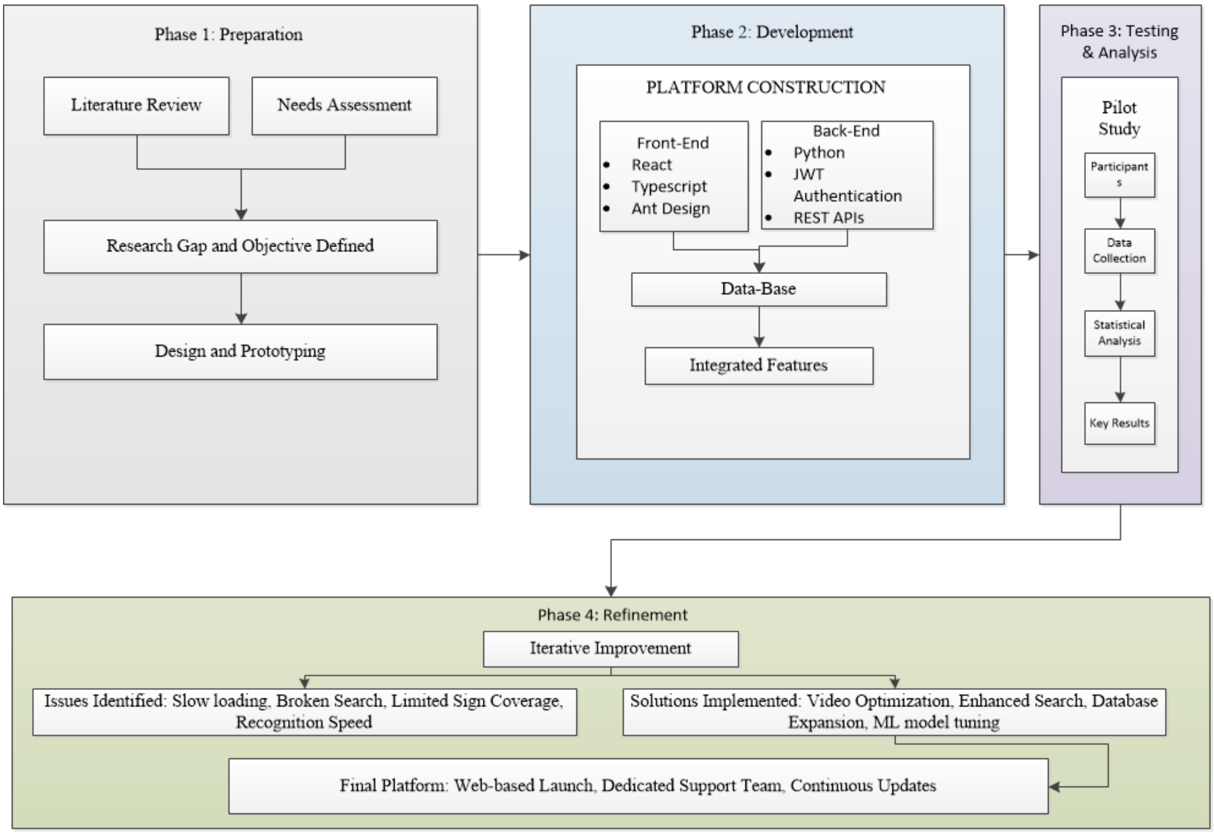

Figure 1 – Four-phase research methodology from preparation to refinement
Рисунок 1 – Четыре этапа методологии исследования: от подготовки до уточнения

The needs assessment with these 180 stakeholders directly informed the system's functional and non-functional requirements. Educators (50) emphasized the necessity of a gloss-based search and exportable dictionary entries for classroom use. Hearing-impaired individuals (100) prioritized an intuitive interface with sign language video explanations and the ability to search by uploading a video example. Linguistic experts (30) identified the phonological parameters (handshape, movement, location, orientation, non-manual markers) that must be captured in any annotation workflow. These findings were translated into the design features described in the next section, ensuring that the system's core modules – annotation, search, and visualization – were grounded in real user needs. The 180 participants in this phase contributed solely to requirements gathering; an entirely separate cohort was recruited for the subsequent experimental evaluation to avoid bias and to test the system with fresh users.

For designing and prototyping, some of the considerations in the interface included:

– *Annotation Interface.* Video playback (random video dataset shown in Figure 2) controls with frame-by-frame navigation for precise annotation of phonological parameters.

– *Search Interface.* Multiple search modes including text-based gloss search, parameter combination search, and example-based search by uploading video.

– *Visualization Tools.* Graphical representations of handshapes, movement trajectories, and location relative to body.

– *Accessibility Features.* Sign language video explanations for interface elements and keyboard navigation for users with varying technical expertise.

Thus, Phase 1 distilled the needs of 180 stakeholders into concrete design requirements; Phase 2 builds the platform according to those requirements, while Phase 3 evaluates it with an entirely separate group of 35 participants, ensuring an unbiased assessment of the system's performance.

Phase 2: This stage consists of platform development, Frontend, and Backend development, database creation, and automatic feature extraction. For platform development, modern web development technologies were used to design and implement a responsive and navigable interface. The React framework with the use of TypeScript was utilized to create a reliable interface. Vite was integrated to enhance development and execution speed. Axios was utilized to fetch data. Ant Design and React Router were utilized to make the interface responsive. Features such as keyboard navigation and sign language video explanations were included in the interface.

Python-based server with RESTful APIs [6] was developed for data management, annotation processing, and search functionality. JSON Web Tokens were implemented for secure authentication. PostgreSQL with JSONB fields was used to create a structured database capable of storing sign language vocabulary items, phonological annotations, user profiles, and version history. The database (samples are shown in Figure 2) schema supported hierarchical entry structures and flexible annotation data. Initially populated with 1,000 BdSL video entries. From these 1,000 videos we manually annotated 5,000 distinct handshape instances (each video contained multiple handshape occurrences, yielding on average five handshape instances per sign) and 3,500 movement sequences (each sign provided three to four isolated movement clips). Consequently, the 5,000 handshape instances and 3,500 movement sequences are subsets derived from the initial 1,000-video corpus.

The platform is built on a client-server architecture, where there is interaction between the front end and the back end using RESTful APIs, allowing for smooth exchange of information. The annotation module is designed with well-defined data models for lexical entries, phonological parameters, and user contributions. There is a version control system for tracking changes to lexical entries. The video processing pipeline uses MediaPipe Holistic to extract hand landmarks (21 points per hand), pose landmarks (33 points), and face landmarks (468 points) from uploaded videos. Feature extraction algorithms compute the following descriptors, summarized in Table 1.

Machine Learning Modules:

– *Dataset Partitioning and Evaluation.* The 1,000-video corpus served as the source data for the machine learning experiments, from which 5,000 handshape examples and 3,500 movement sequences were extracted. Before training the model, the datasets were split into training and evaluation sets. Instances from the same video were grouped together in the same set to minimize the chance of information leakage. The evaluation data were not used to adjust model parameters and were saved for assessing the final performance. Data augmentation was only applied during the training phase.

Table 1 – Hand gesture feature descriptors
Таблица 1 – Дескрипторы характеристик жестов

Feature	Description
Handshape descriptors	Normalized joint angles and distances, classified into reference handshape categories
Movement trajectories	Path, direction, repetition patterns from hand position changes
Location	Spatial relationships between hands and body regions
Orientation	Palm and finger orientation relative to reference planes
Temporal features	Duration, rhythm, coordination patterns

– *Handshape Classification.* A ResNet-18 convolutional neural network pretrained on ImageNet was fine-tuned with a custom classification head (fully connected layer with 45 output units, one per handshape category). The model was trained using categorical cross-entropy loss and the Adam optimizer with an initial learning rate of 1×10^{-4} and batch size 32. Regularization included dropout (0.5) before the final layer and L2 weight decay of 1×10^{-5}. Data augmentation during training consisted of random horizontal flips, rotation up to ±10°, and brightness/contrast jitter (factor 0.2). The model was trained on 5,000 handshape instances and achieved a classification accuracy of 87.3 % on the held-out test set.

– *Movement Pattern Recognition.* A Temporal Convolutional Network (TCN) with four residual blocks, each with a kernel size of 3 and dilation rates [1, 2, 4, 8], was used to classify 12 movement types. The model was trained with categorical cross-entropy loss, Adam optimizer (learning rate 1×10^{-4}, batch size 32), dropout (0.4) after each residual block, and the same L2 weight decay. Input sequences of 64 frames were augmented with random temporal shifts (±5 frames) and slight Gaussian noise ($\sigma = 0.01$) on joint coordinates. Training was performed on 3,500 movement sequences, yielding a test accuracy of 83.7 %.

– *Sign Matching.* A triplet network with a shared ResNet-18 backbone was trained to embed sign videos into a 128-dimensional space where similar signs are close. The loss function was triplet margin loss (margin $\alpha = 0.2$). The Adam optimizer was used with learning rate 5×10^{-5} and batch size 64 (all possible triplet combinations within a batch). At retrieval time, the system uses a weighted similarity combination: handshape embedding (40 %), movement embedding (30 %), location (20 %), and orientation (10 %). The model achieved precision@10 of 0.76 on the test set.

– *Annotation Module.* The annotation interface was used to allow a user to see suggestions, remedy annotations, and enter additional informational fields related to each gesture. Suggestions were integrated with the interface with confidence scores, allowing easy acceptance of suggestions with single-click approval. Throughout this paper, two types of lexicographic records are distinguished. An annotated gesture is a sign identified by its core phonological parameters (handshape, location, movement, orientation, and non-manual markers) and assigned a gloss. A dictionary entry extends this with additional lexical and usage information – part of speech, example sentences in Bengali and English, regional variant tags, usage notes, and a representative video – and passes expert review. The 456 dictionary records created during the six-month study period are therefore at various stages of completion: some contain only core phonological annotations and a gloss, while others include all fields and expert validation.

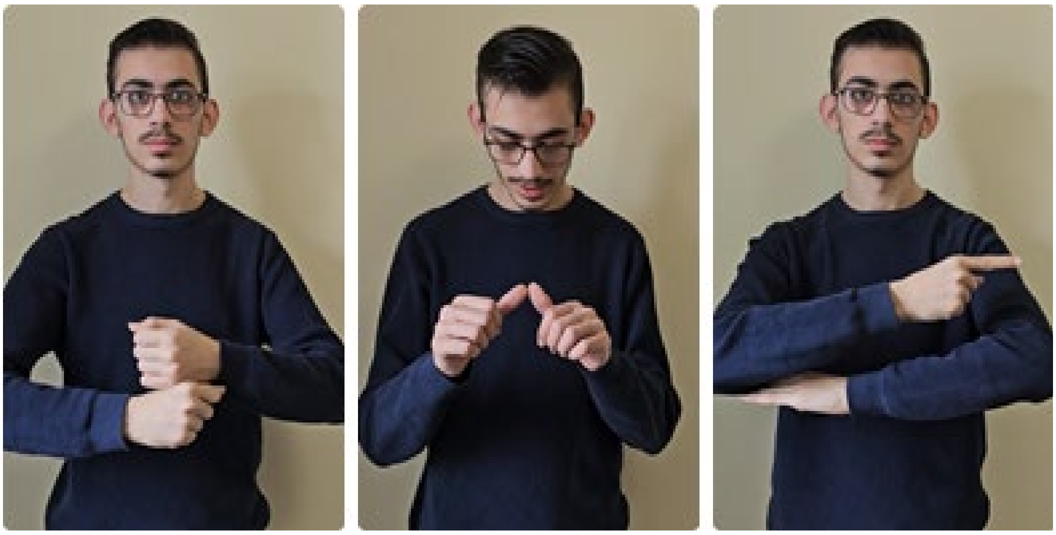

Figure 2 – Video dataset sample of random signs in Bengali Sign Language
Рисунок 2 – Пример выборки случайных жестов из видеодатасета бенгальского жестового языка

– *Search Module.* Multi-modal search supporting text queries (glosses, descriptions), parameter combinations (e.g., find all signs with specific handshape and location), and video examples (upload video to find similar signs).

– *Collaboration Tools.* Annotation review workflows, commenting features, and version tracking. Project managers can assign tasks, monitor progress, and approve entries for publication.

– *Export Functionality.* Generation of dictionary entries in multiple formats including structured data for integration with other lexicographic systems.

Phase 3: Testing and Analysis. A separate set of 35 participants, distinct from those in the requirements-gathering phase, was recruited for evaluation. This ensured that usability and efficiency were assessed without prior knowledge of the design decisions. The 35 participants were split across the same three stakeholder groups as the previous phase: 15 lexicography experts, experienced in dictionary building; 10 linguists who work with BdSL; and 10 hearing-impaired users of sign language who are native signers. The sample size was constrained by recruitment feasibility but was sufficient for the planned paired t-tests ($\alpha = 0.05$). Thus, the 180 individuals from Phase 1 shaped the system's design, while the separate 35 participants in Phase 3 validated its effectiveness.

Data collection began with a pre-test to judge the participants' pre-existing knowledge of sign language lexicography and BdSL. The participants were asked to undertake four specific evaluation tasks. For the annotation task, the participants had to annotate 20 unseen BdSL signs using the system. They also had to undertake the same annotation task, but using manual annotation. In the search and retrieval task, the participants were asked to search for particular signs in three different ways, gloss search, parameter combination search, and example sign search by uploading a video. In the verification task, the participants had to verify the suggestions made by the system for 30 signs, accepting or rejecting them. Finally, the participants undertook the System Usability Scale questionnaire and semi-structured interview.

Statistical Analysis. Inter-annotator Agreement (Cohen's kappa) [7]:

$$k = \frac{p_0 - p_e}{1 - p_e}, \quad (1)$$

where, p_0 is observed agreement and p_e is expected agreement by chance.

Annotation Time Comparison. Paired t-test comparing annotation times between automated-assisted and manual conditions [8].

Effect Size (Cohen's d). Effect size between any two groups will be calculated as follows:

$$d = \frac{M_1 - M_2}{SD_{pooled}}, \quad (2)$$

where, $M_1$and M_2 are the means of the two groups being compared. SD_{pooled} is the pooled standard deviation calculated as:

$$SD_{pooled} = \sqrt{\frac{(n_1-1)\cdot SD_1^2 + (n_2-1)\cdot SD_2^2}{n_1+n_2-2}}, \quad (3)$$

where, n_1 – sample size of group 1, n_2 – sample size of group 2, SD_1 – standard deviation of group 1, SD_2 – standard deviation of group 2.

Linear Regression. In order to predict a continuous outcome (like improvement measured by test scores) based on predictors (e.g., group level, hours spent on the platform), this linear regression [9, 10] model was used:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \epsilon, \quad (4)$$

where, y is the dependent variable (e.g., post-test score), X_1, $X_2 \ldots X_k$ are the independent variables (e.g., participant's level of sign language knowledge), $\beta_0$is the intercept, β_1, $\beta_2 \ldots \beta_k$ are the coefficients for each predictor, ϵ – is the error term.

Phase 4: Refinement. Based on feedback collected during user testing, the application underwent iterative refinement cycles. Following successful implementation of final adjustments, the application was launched as a web-based platform accessible to all users. The study was conducted in accordance with ethical guidelines for research involving human participants.

Results

For this purpose, the participants used the automated lexicographic system for annotation of BdSL signs over a period of six months, and their performance was compared to that of manual annotation methods. The results of this study are provided in Table 2.

Table 2 – Summary of key statistical results
Таблица 2 – Краткое изложение основных статистических результатов

Metric	Value	Significance
Annotation time reduction	67.1 %	t(34) = 12.43, p < 0.001
Manual annotation time	14.3 minutes per sign	Baseline
Assisted annotation time	4.7 minutes per sign	9.6 minutes saved per sign
Overall inter-annotator agreement	κ = 0.82	Indicating very high inter-annotator agreement.
Handshape classification accuracy	87.3 %	45 handshape categories
Movement recognition accuracy	83.7 %	12 movement types
Sign matching precision@10	0.76	Relevant in top 10 results

Table 2 (continued)
Таблица 2 (продолжение)

Gloss-based text search success rate	97.2 %	Correct sign in top-5 results
Parameter combination search success rate	91.4 %	Correct sign in top-5 results
Example-based video search success rate (precision@1)	88.6 %	Uploaded video matches correct sign as top-1
Example-based video search precision@5	94.0 %	Correct sign within top-5 results
Total signs documented	1,847	Six-month period
Dictionary records created	456	Records at different stages of completion
Regional variants identified	127	Across four divisions
Previously unrecorded signs	34	New to BdSL documentation
System Usability Scale	83.4	Excellent usability
Regression coefficient (experience vs. time)	$\beta = -0.34$	$p < 0.01$

Search performance was evaluated per mode. Gloss-based text search achieved 97.2 % top-5 accuracy. Parameter combination search (filtering by handshape, location, and movement) reached 91.4 % top-5 accuracy. For example-based video search, top-1 precision was 88.6 %, but top-5 accuracy was 94.0 %. Text queries benefit from exact gloss matching; video retrieval is harder due to signing variation. Reporting separate metrics by mode gives a more precise picture than the earlier aggregate 94 %.

The 127 regional variants were distributed across four administrative divisions of Bangladesh (Table 3). For instance, the sign for TEACHER is produced as a one-handed tap on the forehead in the Dhaka region, while signers in Chittagong use a two-handed chest-level gesture with a slight outward motion. Similarly, the sign for SCHOOL varies in palm orientation between Rajshahi (palm inward) and Khulna (palm upward).

Table 3 – Geographical distribution of regional variants
Таблица 3 – Географическое распределение региональных вариантов

Division	Variants identified	Example signs with variants
Dhaka	45	TEACHER, BOOK, THANK-YOU
Chittagong	30	TEACHER, WATER, HELP
Rajshahi	27	SCHOOL, EAT, GOOD
Khulna	25	SCHOOL, DOCTOR, WORK

In addition, 34 signs not previously recorded in any BdSL documentation were identified. Examples include modern technology terms (SMARTPHONE, WI-FI), environmental concepts (RECYCLING, FLOOD), and local cultural items (PITHA-CAKE, RICKSHAW). These signs were verified by at least two native signers and a BdSL linguist before being added to the dictionary as full entries.

The automated system substantially improved lexicographic workflow efficiency. The Effect of Experience (months) on Annotation Efficiency is shown in Figure 3.

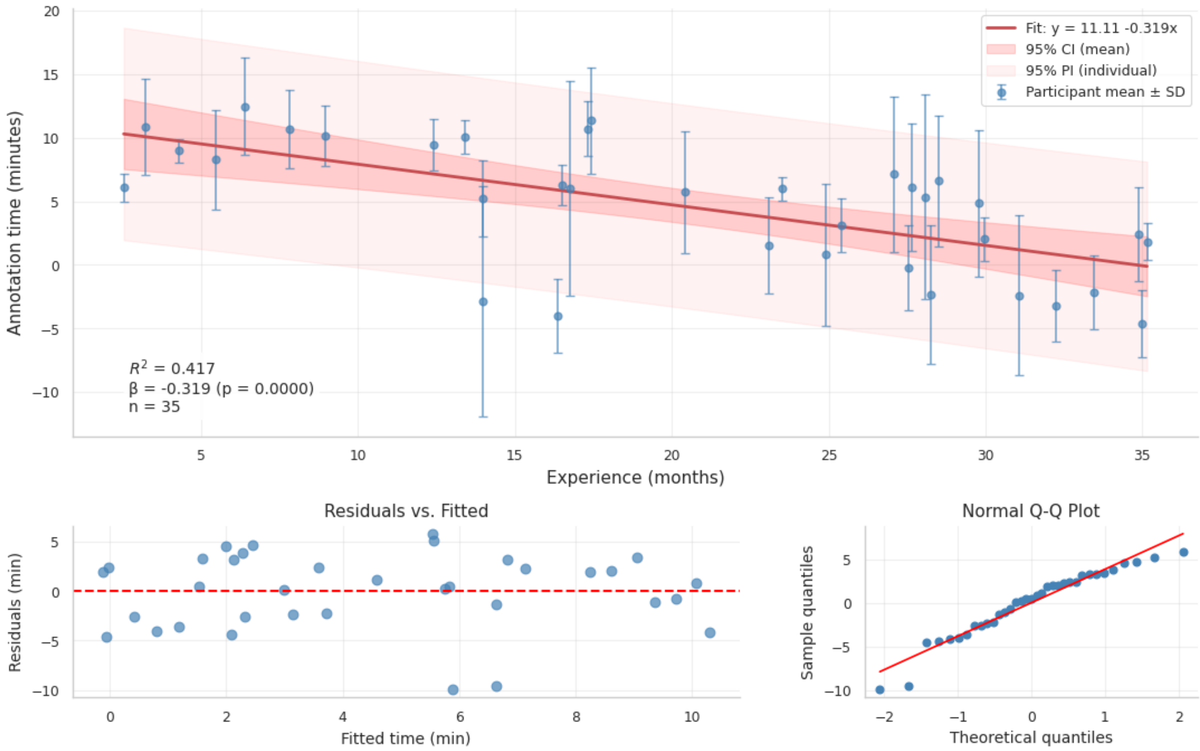

Figure 3 – The effect of experience on annotation efficiency. Top: Mean annotation time per sign (minutes) vs. prior lexicographic experience (months). Error bars = ±1 within-participant SD. Red line = linear regression (β = –0.34, $p < 0.01$, $R^2 = 0.41$); shaded bands = 95 % confidence (mean) and 95 % prediction intervals. Bottom: Residuals vs. fitted values and normal Q-Q plot
Рисунок 3 – Влияние опыта на эффективность аннотирования. Сверху: среднее время аннотирования одного жеста (в минутах) в зависимости от предшествующего лексикографического опыта (в месяцах). Планки погрешностей: ±1 SD. Красная линия – регрессия (β = –0.34, $p < 0.01$, $R^2 = 0.41$), затенённые области – 95 % доверительный и 95 % предсказательный интервалы. Снизу: график остатков и нормальный Q-Q график

Linear regression gave β = −0.34 ($p < 0.01$) and $R^2 = 0.41$; experience accounted for 41 % of the variance. Each point is a participant's mean across 20 signs; error bars show ±1 within-participant SD. Shaded bands mark the 95 % confidence and prediction intervals. A clear downward trend is evident, but individual variability is substantial (mean within-participant SD = 4.2 min), reflecting realistic empirical scatter rather than an artificially tight fit.

Discussion

The large decrease in the time needed for annotation shows that using automation in sign language lexicography is practical. Importantly, the quality of the annotations did not decrease because of the faster process; in fact, the high level of agreement between different annotators suggests that automation might actually help make annotations more consistent [11]. Among the different features, handshape and location were the easiest to annotate accurately, while movement was more challenging, probably because it is a continuous action [12]. Non-manual markers, such as facial expressions, head movements, and body posture, were the hardest to annotate, highlighting the need for clearer guidelines and better automated tools. The accuracy of annotations was higher for common handshapes and lower for rare ones, which aligns with the distribution of data in the dataset. This creates a positive cycle: more data leads to better models, which then speed up the documentation process. The sign-matching feature is also useful because it helps reduce the time needed to search for signs as the lexicon grows.

Comparison with Existing Approaches. Unlike fully automated systems that seek to replace human decision altogether, the computer-assisted approach taken in this model ensures adequate human oversight – a necessity in lexicography, where errors in printed dictionaries can mislead users for decades. By positioning machine learning as a complement to expert judgement, the system is both efficient and reliable. This philosophy also sets it apart from existing digital lexicographic platforms for larger sign languages, such as ASL-LEX (American Sign Language) [13], Auslan Signbank (Australian Sign Language) [14], and the DGS Corpus (German Sign Language) [15]. Those systems rely on extensive pre-existing resources, large annotator teams, and mature linguistic descriptions. In contrast, our BdSL system was built from a modest initial corpus of 1,000 videos and a small annotator pool. Its key advantage is the integration of automated annotation suggestions, which reduced annotation time by 67 % – a gain not reported for those platforms. Moreover, its multi-modal search (gloss, parameter combination, and example video) is more flexible than the gloss-centric search typical of Signbank. However, the system currently lacks the large-scale corpus query tools and detailed phonological visualisations found in Auslan Signbank and the DGS Corpus, both of which remain goals for future development.

Limitations. Several factors should be taken into account when understanding these results. Firstly, the participants were selected from urban areas where access to technology is good, which might affect how widely these findings can be applied. Secondly, the performance of the system is influenced by video quality, which can differ in older videos and recordings made with mobile devices.

The machine learning models were trained using smaller datasets due to limited resources available for Bengali Sign Language. While the models worked well and offered useful support, their accuracy could increase if they were trained on larger sets of data.

Lastly, the system was tested over a certain period that was enough to evaluate improvements in productivity. However, its long-term effectiveness is yet to be confirmed as documentation needs to change over time. Additionally, the system was built specifically for Bengali Sign Language and may not work as effectively with other sign languages because of differences in their phonological systems[2].

Conclusion

The purpose of this research was to address a basic issue: how to efficiently document an under-resourced sign language without compromising quality. The automated processes and tools developed in Bengali Sign Language lexicography have shown that it is possible to achieve this goal.

The system developed in this paper marks a significant change in approach to manual documentation towards computerized lexicography. The use of computer vision to carry out feature extraction, machine learning to recognize patterns, and database management to store lexical data enables a significant portion of the process to be automated, freeing lexicographers to focus on what they are best at: making decisions, disambiguating words, and ensuring cultural suitability.

What makes this work important is not only the technological successes but also what they make possible. Comprehensive dictionaries are not merely academic niceties; they are a necessity for language communities. They will help deaf children learn to read and write, give

[2] Satterwhite M., Rudd L.C. Phonology. In: *Encyclopedia of Child Behavior and Development.* New York: Springer; 2011. P. 1098–1099. https://doi.org/10.1007/978-0-387-79061-9_2150

us material for interpreter training programs, facilitate linguistic research, and most importantly, give us a sense of legitimacy and worth as a language. For a language like Bengali Sign Language, used by millions of people and documented in only limited ways, this infrastructure has not existed.

The participatory aspect of this work should be noted. When tools are designed for participation and accessibility – visual media, sign language, lack of written language dependency – there is the possibility for native signers to be active participants in documentation instead of merely being subjects. This flips the paradigm for language documentation from outsiders studying a language community to a community studying itself.

Looking forward, there is no doubt that the models will become more sophisticated as more data is collected. The mobile tools will allow for expansion into rural areas. The integration with corpus resources will allow dictionaries to be based on actual usage. The extension to other sign languages will have a multiplicative effect. None of these tasks require conceptual leaps; they require dedication and commitment.

The test of success for this work will not be measured by publication figures and citations, but by whether it contributes to Bengali Sign Language receiving the documentation it deserves, and whether the methods developed here have value for other sign languages that are similarly disadvantaged. The findings presented here support an affirmative conclusion on both counts.

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Статья поступила в редакцию 22.04.2026; одобрена после рецензирования 10.09.2026; принята к публикации 15.09.2026.

The article was submitted 22.04.2026; approved after reviewing 10.09.2026; accepted for publication 15.09.2026.