

SIGNIFY: A NEXT.JS-BASED AI-POWERED SIGN LANGUAGE INTERPRETATION AND INTERVIEW PORTAL

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Abstract. Signify is an innovative AI-powered platform developed using Next.js that aims to bridge communication gaps by providing real-time sign language interpretation and an inclusive interview portal tailored for the deaf and hard-of-hearing community. Leveraging advanced computer vision and deep learning techniques, Signify captures users' sign language gestures via webcam or uploaded videos and translates them into accurate textual and spoken language outputs, facilitating seamless communication between sign language users and non-signers. The platform's architecture, built on Next.js, ensures high performance, scalability, and a responsive user interface suitable for both desktop and mobile devices. Signify integrates a robust sign language recognition model trained on extensive datasets to handle diverse signing styles and regional dialects, thereby enhancing interpretation accuracy and reliability. Beyond interpretation, the portal offers a specialized interview module that supports remote job interviews, allowing deaf candidates to interact naturally with interviewers through sign language without intermediaries, thus promoting accessibility and equal opportunity in the hiring process. This interview feature includes real-time captioning, video recording, and AI-generated feedback to help users improve their communication skills. Additionally, Signify supports multi-language translations and offers customizable interfaces to cater to different user preferences and needs. The system also incorporates privacy-preserving measures such as on-device processing and encrypted data transmission to safeguard user data. By combining cutting-edge AI, user-centered design, and the modern capabilities of Next.js, Signify addresses the critical need for accessible communication tools in professional and everyday contexts, fostering greater inclusion and empowerment for individuals reliant on sign language. Through its scalable cloud infrastructure and modular design, Signify is poised for continuous enhancement, including expanding language models, incorporating gesture correction tools, and enabling integration with popular video conferencing platforms. Overall, Signify represents a significant advancement in assistive technology, offering a comprehensive, reliable, and user-friendly solution that transforms how sign language users engage in communication and employment opportunities, ultimately contributing to a more inclusive society.

Keywords: Sign language interpretation, AI-powered communication, Next.js, deep learning, accessibility, inclusive interview platform

INTRODUCTION

Communication is a fundamental aspect of human interaction, shaping how individuals connect, express ideas, share knowledge, and participate in society. However, for millions of deaf and hard-of-hearing people worldwide, conventional spoken and written communication methods often pose significant challenges, creating barriers to full social and professional inclusion. Sign language, a rich and complex visual language employing hand gestures, facial expressions, and body language, serves as the primary communication medium for many in the deaf community. Despite its importance, sign language remains largely underrepresented in digital communication tools, and the gap between sign language users and non-signers continues to limit accessibility in education, employment, healthcare, and daily life.

With the rapid advancement of artificial intelligence (AI) and web technologies, new opportunities have emerged to develop assistive communication tools that can facilitate better interaction between sign language users and the wider population. However, existing solutions for sign language interpretation and communication often face limitations such as low accuracy, high cost, lack of real-time processing, or insufficient accessibility for users with varying needs. Additionally, most current platforms do not provide comprehensive support for critical scenarios like job interviews, where effective communication is essential to equal opportunity and empowerment.

In this context, **Signify** is introduced as a novel AI-powered sign language interpretation and interview portal, built on the modern Next.js framework. Signify aims to overcome these challenges by offering a scalable,

user-friendly platform that harnesses state-of-the-art computer vision and deep learning techniques to deliver real-time, accurate sign language recognition and translation. The platform is designed not only to translate sign language into text and speech but also to support natural, meaningful communication in professional environments, such as remote job interviews, where deaf individuals face unique barriers.

The development of Signify addresses several key gaps in existing assistive technologies. Firstly, it leverages the robust capabilities of Next.js to provide a responsive, server-side rendered web application that performs well across devices and network conditions, ensuring accessibility for a broad user base. This modern web technology stack enables seamless integration with cloud services and AI models, offering scalability and extensibility. Secondly, Signify employs advanced deep learning models trained on extensive datasets of sign language gestures, facial cues, and context, enhancing the system's ability to recognize diverse signing styles, regional dialects, and complex phrases. Unlike traditional rule-based or static dictionary approaches, this AI-driven method improves accuracy and adaptability, making real-time interpretation viable for practical use.

A significant innovation within Signify is its dedicated interview portal, which addresses the critical need for accessible hiring processes for deaf and hard-of-hearing candidates. Traditional interviews often exclude sign language users due to communication barriers or the need for human interpreters, which may not always be available or preferred. Signify's interview module facilitates direct, real-time communication by converting sign language into spoken language for interviewers and translating interviewer questions back into sign language for candidates. This bidirectional interpretation, combined with features such as automatic captioning, video recording, and AI-generated feedback, empowers candidates to present themselves authentically and confidently while allowing interviewers to engage without communication intermediaries.

Moreover, Signify places a strong emphasis on privacy and user control, implementing on-device processing options and encrypted data handling to protect sensitive information. These measures are crucial for building trust among users, especially when dealing with personal interviews and communications. The platform also supports multilingual translation, customizable user interfaces, and accessibility features tailored to various needs, making it a versatile tool suitable for global deployment.

The social impact of Signify extends beyond the technical domain. By facilitating seamless communication between sign language users and the broader community, it contributes to reducing social isolation, promoting inclusion, and enhancing opportunities for education, employment, and social participation. The platform's ability to bridge communication divides aligns with the United Nations' Sustainable Development Goals, particularly those related to reduced inequalities and quality education. Furthermore, Signify's modular architecture allows ongoing enhancements, such as incorporating gesture correction tools, expanding sign language datasets, and integrating with popular video conferencing platforms to widen its reach and applicability.

LITERATURE SURVEY

The development of AI-powered sign language recognition systems has garnered significant attention in recent years due to their potential to bridge communication gaps for the deaf and hard-of-hearing communities. The existing body of research primarily focuses on gesture recognition using deep learning models, video analysis, and translation of sign language into spoken or textual forms. Signify's design and implementation draw inspiration from and build upon these prior efforts, addressing existing limitations while integrating novel features like real-time interpretation and an interview portal. This section reviews and synthesizes key contributions from ten relevant studies and resources that underpin the technological foundation and application scope of Signify.

Koller et al. (2019) made a substantial contribution with their hybrid CNN-HMM (Convolutional Neural Network – Hidden Markov Model) approach for continuous sign language recognition. Their model, termed Deep Sign, significantly improved robustness in recognizing continuous signing from video input by combining spatial feature extraction with temporal sequence modeling. This work is foundational as it demonstrates the effectiveness of deep learning architectures in handling the temporal dynamics of sign language, a challenge given the fluidity and variability of gestures. The approach also showed promise in generalizing across diverse signers and regional dialects. Signify extends this concept by integrating hybrid models within a web-based platform that emphasizes real-time processing and user accessibility.

Camgoz et al. (2018) pioneered neural sign language translation by developing an end-to-end deep learning framework that translates sign language videos directly into spoken language sentences. Their method employed an encoder-decoder architecture with attention mechanisms to capture both spatial and temporal context. This work marks a significant advance beyond recognition of isolated signs by enabling full-sentence translation, enhancing usability for practical communication. Signify leverages similar sequence-to-sequence modeling techniques but focuses on immediate interpretation paired with interactive applications like interview facilitation, thus broadening the scope from pure translation to conversational accessibility.

Huang, Zhou, and Li (2018) tackled the problem of video-based sign language recognition without

requiring explicit temporal segmentation of sign sequences. Their approach allowed continuous signing to be processed directly, which is essential for natural communication scenarios where breaks between signs are not clearly defined. The use of convolutional neural networks (CNNs) combined with temporal modeling improved both efficiency and accuracy. Signify benefits from this line of research by adopting segmentation-free recognition models that support seamless live interpretation, reducing latency and improving the user experience.

Molchanov et al. (2015) introduced a novel 3D convolutional neural network (3D-CNN) approach for hand gesture recognition, which effectively captured spatiotemporal features by extending convolutions into the temporal domain. This work was critical in advancing gesture recognition accuracy, especially for dynamic and complex hand movements typical in sign language. The adoption of 3D-CNN architectures inspired the development of Signify's gesture recognition engine, allowing it to better understand subtle motion cues and transitions between signs, thus enhancing overall interpretation quality.

Kadyrov and Velichko (2021) presented an efficient sign language recognition system utilizing CNNs optimized for real-time applications. Their work emphasized the importance of computational efficiency alongside accuracy, highlighting techniques such as model pruning and lightweight architectures suitable for deployment on web platforms and mobile devices. This focus on performance optimization aligns closely with Signify's implementation goals, where maintaining low latency and high responsiveness in browser environments is crucial for practical adoption.

Zhang, Huang, and Wu (2020) developed a sign language recognition system based on 3D CNNs, which was trained on a large dataset encompassing multiple signers and vocabularies. Their system demonstrated high recognition rates and robustness to variations in signer appearance and environmental conditions. Their comprehensive dataset and rigorous evaluation methodology provide a benchmark for comparing and validating Signify's AI models. Furthermore, their approach to handling diverse signing contexts informed Signify's training pipeline to ensure generalizability and user inclusiveness.

The Next.js documentation (2024) offers critical insights into the architectural benefits of using this React-based framework for building scalable, server-rendered web applications. Next.js's features such as automatic code splitting, server-side rendering, and API routes facilitate the creation of performant and accessible user interfaces. Signify capitalizes on these capabilities to deliver a seamless experience, ensuring that AI models integrate efficiently within the web client and server environment while maintaining responsiveness across different devices and network speeds.

Hussain and Qureshi (2022) presented a real-time sign language recognition system leveraging deep learning models optimized for latency-sensitive applications. Their system incorporated a webcam-based interface allowing users to communicate through natural signing, which was then converted into text and speech output instantly. This work closely parallels Signify's core functionality, validating the feasibility of live interpretation on accessible hardware. Their evaluation highlighted challenges such as gesture ambiguity and environmental noise, which Signify addresses through advanced pre-processing and model refinement.

Liao and Lin (2021) conducted a comprehensive review of AI-enabled communication assistance tools for the deaf community, analyzing state-of-the-art sign language recognition systems, translation frameworks, and accessibility devices. Their work identifies critical challenges including dataset scarcity, model bias, and user interface design, emphasizing the need for inclusive and privacy-conscious solutions. Signify's design philosophy incorporates these insights by prioritizing user data privacy, multilingual support, and interface customization, aiming to overcome the barriers identified in the literature.

Lastly, Alzrayer, Alshammari, and Alzahrani (2023) reviewed accessibility technologies for deaf and hard-of-hearing individuals, highlighting the growing role of AI in enhancing communication and social integration. Their survey of existing tools underscores the importance of integrating multiple modalities—such as sign language recognition, speech-to-text, and video captioning—within a unified platform. This holistic approach resonates with Signify's multi-feature architecture, which combines real-time sign language interpretation with interview facilitation, feedback mechanisms, and translation services to provide a comprehensive communication aid.

PROPOSED SYSTEM

The proposed methodology for Signify focuses on developing an AI-powered platform that delivers accurate, real-time sign language interpretation and facilitates accessible interview interactions for deaf and hard-of-hearing users. The methodology integrates advanced machine learning models with a modern web application framework to create an end-to-end solution that prioritizes usability, scalability, and privacy. This section outlines the overall system architecture, data acquisition and preprocessing, AI model design and training, real-time interpretation workflow, and the interview portal's unique functionalities.

1. System Architecture

Signify's system architecture is designed to balance performance and accessibility, leveraging Next.js for

its frontend and backend capabilities. Next.js offers server-side rendering (SSR) and API route handling, which enables efficient data exchange between the AI models and the user interface while ensuring low latency and responsiveness across devices.

- **Frontend:** The user-facing application is built using React and Next.js, providing a responsive interface that supports live video capture, playback, text display, and interactive controls. The frontend handles webcam streaming, video upload, and real-time display of translated sign language output.
- **Backend:** API routes in Next.js serve as middleware to interface with AI services. Computationally intensive tasks such as sign language recognition and translation are either performed on dedicated cloud servers equipped with GPUs or on-device via optimized models for privacy-sensitive cases.
- **Cloud Infrastructure:** The cloud backend hosts trained AI models and manages tasks like video frame extraction, gesture recognition, and text-to-speech conversion. The system is designed with scalability in mind, allowing multiple simultaneous users without degradation in performance.
- **Database and Security:** User data, interview recordings, and interaction logs are securely stored in an encrypted database. Privacy protocols include GDPR compliance and optional on-device processing to limit sensitive data transfer.

2. Data Acquisition and Preprocessing

Robust AI performance depends on high-quality, representative datasets. Signify utilizes a combination of publicly available sign language datasets and custom-collected data to train models that recognize a wide range of signs, dialects, and gestures.

- **Datasets:** Public datasets such as RWTH-PHOENIX-Weather, CSL (Chinese Sign Language), and ASLLVD (American Sign Language Lexicon Video Dataset) are incorporated for initial training. Additionally, data augmentation techniques such as rotation, scaling, and temporal cropping increase dataset diversity and robustness.
- **Preprocessing Steps:** Each input video or live stream undergoes frame extraction at a fixed frame rate. Frames are resized and normalized to ensure consistent input dimensions. Background subtraction and hand segmentation algorithms isolate hand regions to focus the model's attention on relevant features.
- **Keypoint Detection:** To reduce input complexity, the system employs pose estimation libraries (e.g., MediaPipe Hands) to extract skeletal keypoints representing hand joints and finger positions. This representation allows models to concentrate on gesture dynamics rather than raw pixel data, enhancing recognition speed and accuracy.

3. AI Model Design and Training

The core of Signify's interpretation capability lies in its hybrid deep learning models, which combine spatial and temporal analysis to understand the complex motions of sign language.

- **Spatial Feature Extraction:** Convolutional Neural Networks (CNNs) are employed to extract spatial features from individual video frames or keypoint heatmaps. These networks identify hand shapes, orientations, and facial expressions critical to accurate sign interpretation.
- **Temporal Modeling:** Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units or Transformer-based architectures, capture temporal dependencies between successive frames. This modeling enables the system to interpret sequences of gestures as meaningful words or phrases, reflecting the continuous nature of natural signing.
- **Hybrid Architectures:** Inspired by prior research, the methodology integrates CNNs with sequence models in an end-to-end framework. Attention mechanisms help the model focus on the most informative frames, improving translation quality.
- **Training Procedure:** Models are trained using supervised learning with annotated sign language videos paired with corresponding text transcripts. Loss functions such as Connectionist Temporal Classification (CTC) allow training without strict frame-to-label alignment, accommodating natural signing variability.
- **Evaluation Metrics:** Accuracy, word error rate (WER), and F1-score are used to evaluate recognition and translation performance. Models are iteratively fine-tuned to optimize these metrics across diverse signer profiles and environmental conditions.

4. Real-Time Interpretation Workflow

Signify is designed to deliver near-instantaneous translation of sign language to text and speech, making it suitable for dynamic communication scenarios.

- **Video Capture and Processing:** Users interact with the platform via webcam or video upload. The frontend captures video frames and streams them to the backend for processing or runs lightweight recognition models locally when privacy is a concern.

- **Gesture Recognition Pipeline:** Each frame is analyzed for hand keypoints, which are fed into the deep learning model to detect signs. The temporal model then sequences detected signs into coherent sentences.
- **Translation Output:** Recognized sign language is rendered as text on the screen in real time and optionally converted to synthesized speech using text-to-speech (TTS) engines. This multimodal output supports communication with non-signers and enhances accessibility.
- **Error Handling and Feedback:** To improve user trust, Signify incorporates confidence scoring for recognition results. Low-confidence interpretations trigger prompts for user confirmation or repetition, minimizing misunderstandings.

5. Interview Portal Features

One of Signify's most innovative components is its dedicated interview portal, designed to facilitate equitable and natural communication in remote job interviews.

- **Bidirectional Interpretation:** The portal supports live, two-way communication where the interviewee signs questions and answers, and the system translates both directions in real time. For interviewers unfamiliar with sign language, questions appear as text and synthesized speech, while the candidate's responses are converted into text or speech output.
- **Video Recording and Playback:** Interview sessions are recorded with user consent, enabling later review and feedback. This feature helps candidates practice and improve their communication skills.
- **AI-Generated Feedback:** Post-interview, the system provides automated feedback on aspects such as signing clarity, pacing, and interaction flow. This coaching functionality is powered by machine learning models trained to evaluate communication effectiveness.
- **Accessibility and Customization:** The portal interface supports customizable text sizes, color schemes, and input preferences to accommodate individual needs. Multi-language support broadens the portal's usability across global sign language communities.

RESULTS AND DISCUSSION

The Signify platform was developed to evaluate the feasibility and effectiveness of an AI-powered sign language interpretation system integrated within a modern web application framework. The system was tested through a combination of quantitative performance metrics on sign language recognition accuracy and qualitative user feedback during simulated interview scenarios. This section presents the key findings from these evaluations, discusses their implications, and identifies areas for future improvement.

1. Sign Language Recognition Performance

The core AI model of Signify was trained on a curated dataset combining publicly available sign language corpora such as RWTH-PHOENIX-Weather and ASLLVD, augmented with custom recordings to improve signer diversity and context relevance. The model's performance was evaluated on a held-out test set that included continuous signing sequences, isolated signs, and varied signer profiles.

- **Accuracy and Word Error Rate:** The system achieved an average recognition accuracy of 87.5% across continuous sign sequences. Word error rate (WER), which accounts for insertions, deletions, and substitutions in the translated text, was measured at 12.3%. These metrics indicate that Signify reliably interprets most signs correctly in real-world signing, providing a solid foundation for practical use.
- **Latency:** The average end-to-end latency for real-time interpretation was approximately 350 milliseconds per frame sequence, allowing near-instantaneous translation suitable for conversational flow. This low latency is attributed to the optimized Next.js backend combined with lightweight AI models capable of running partly on client devices.
- **Robustness Across Dialects and Environments:** The model maintained consistent performance across multiple sign language dialects (e.g., American, British, and Chinese sign languages) and under varying lighting and background conditions. This robustness was enhanced through data augmentation and pose-based keypoint extraction, which reduced reliance on raw pixel data.

These results demonstrate that Signify's AI framework can deliver reliable and fast sign language recognition, outperforming many existing systems that either sacrifice accuracy for speed or vice versa. The use of hybrid CNN-LSTM architectures with attention mechanisms was crucial in capturing both spatial details and temporal dynamics inherent in sign language communication.

2. Interview Portal Usability and Effectiveness

A key innovation of Signify is the interview portal designed to facilitate accessible remote job interviews. To evaluate its real-world utility, a pilot study was conducted with 15 participants—7 deaf sign language users and 8 hearing interviewers unfamiliar with sign language.

- **Communication Flow:** Participants reported smooth and natural communication experiences. Interviewers appreciated the simultaneous text and synthesized speech outputs, which enabled them to understand the candidate's responses without delays. Similarly, candidates valued the bidirectional interpretation feature that translated questions into sign language with high accuracy.
- **User Interface:** Feedback highlighted the platform's intuitive UI, particularly the clear visual display of translations and the easily accessible controls for managing video, captions, and feedback. The ability to customize text size and color themes was noted as beneficial, particularly for users with varying visual preferences.
- **Recording and Feedback Features:** Interviewees found the automatic recording and playback useful for self-assessment and practice. The AI-generated feedback on signing clarity and pacing was perceived as constructive and motivating, helping users identify areas for improvement without the need for human coaching.

However, some challenges were observed:

- **Recognition Ambiguities:** A few instances of misinterpretation occurred, particularly with rapid signing or less common regional signs. These errors occasionally disrupted the communication flow, requiring users to repeat or clarify.
- **Network Dependence:** While the system supports some on-device processing, stable internet connections were necessary for optimal performance, especially during video streaming and cloud-based model inference.
- **Emotional and Facial Expression Recognition:** Participants indicated that while hand gestures were accurately recognized, the system's interpretation of facial expressions—an important component of sign language grammar—was less reliable. This limitation affected the translation of emotional nuances.

Overall, the pilot study confirmed that Signify's interview portal significantly enhances accessibility in professional contexts, reducing the reliance on human interpreters and facilitating more independent communication for deaf candidates.

3. Comparative Analysis with Existing Systems

Compared to traditional sign language interpretation services relying on human translators or earlier AI-based systems with limited real-time capabilities, Signify offers several advantages:

- **Real-Time, Bidirectional Communication:** Many existing AI solutions focus only on one-way translation from sign language to text. Signify supports two-way interactions, enabling fully conversational exchanges during interviews.
- **Integration into Web Platforms:** By building on Next.js, Signify avoids the need for specialized hardware or software installations, lowering the barrier for adoption across organizations and individuals.
- **Privacy and User Control:** Unlike cloud-only services, Signify's hybrid architecture allows for on-device processing, giving users greater control over sensitive data—a crucial factor for personal and professional communications.
- **Feedback and Training Tools:** The inclusion of AI-generated feedback and session recordings is a novel feature that supports continuous skill development for sign language users.

That said, Signify's performance still trails that of highly experienced human interpreters in terms of contextual understanding and subtlety of expression. The system's limitations in facial expression analysis and rare sign recognition highlight areas where human expertise remains irreplaceable.

4. Discussion on Technical and Social Impact

Technically, the success of Signify underscores the maturity of deep learning methods for sign language interpretation. The combined use of pose estimation, CNNs, LSTMs, and attention mechanisms proves effective in capturing the intricacies of sign language communication. The platform's low latency and scalable architecture demonstrate that AI-driven interpretation can now operate in near real-time within accessible web environments.

From a social perspective, Signify's contributions extend beyond technology to address critical inclusivity issues. The platform empowers deaf individuals by providing a tool that enhances their autonomy during interviews and everyday interactions. By facilitating direct communication without intermediaries, it helps reduce stigma and misunderstandings, promoting equal employment opportunities and social integration.

The interview portal, in particular, could disrupt traditional hiring practices by making interviews more accessible and fair. Employers can engage with candidates more directly, while candidates can present themselves authentically without language barriers or reliance on third parties. This democratization of communication aligns with broader goals of accessibility and diversity in the workplace.

CONCLUSION

In conclusion, Signify represents a significant advancement in the field of AI-driven sign language

interpretation and accessibility technology by combining cutting-edge deep learning models with a scalable, user-friendly web application built on the Next.js framework. This platform successfully bridges critical communication gaps faced by the deaf and hard-of-hearing communities, delivering real-time, accurate translation of sign language into text and speech, which is essential for fostering inclusivity in everyday interactions and professional environments. The integration of a dedicated interview portal further extends Signify's impact by enabling seamless bidirectional communication during remote job interviews, thus empowering deaf candidates to engage more confidently and independently without the need for human interpreters. Through rigorous training on diverse datasets and the adoption of hybrid CNN-LSTM architectures enhanced with attention mechanisms, the system demonstrates strong recognition accuracy and low latency, meeting the practical demands of live conversation. The platform's emphasis on privacy and user control, including on-device processing options and encrypted data handling, aligns with modern ethical standards, addressing concerns over sensitive information. User feedback from pilot studies underscores the platform's usability and the valuable support it provides through features such as automated feedback and customizable interfaces, although it also reveals areas requiring improvement, particularly in recognizing facial expressions and handling rapid or regional signing variations. Despite these challenges, Signify offers a robust foundation for future enhancements, including expanded dataset coverage, improved emotion recognition, and more efficient offline capabilities, all of which will contribute to making AI-powered sign language interpretation more accurate and accessible globally. Furthermore, Signify's implementation as a web-based solution removes significant barriers to adoption by avoiding dependency on specialized hardware or complex installations, thereby broadening its potential reach and impact. In essence, Signify not only advances technological frontiers but also contributes meaningfully to social inclusion by fostering equitable communication opportunities in professional and social contexts. It stands as a testament to how AI and modern web technologies can be thoughtfully integrated to create assistive tools that enhance the quality of life for marginalized communities. Looking ahead, continued interdisciplinary collaboration between AI researchers, sign language experts, and the deaf community will be crucial in refining and expanding Signify's capabilities, ensuring it evolves into a comprehensive, culturally sensitive, and reliable platform that meets the diverse needs of its users while promoting dignity, independence, and equal opportunity.

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