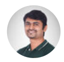
AI-Driven Novel Approach for Enhancing E-Commerce Accessibility through Sign Language Integration in Web and Mobile Applications

Conference Paper · December 2024

DOI: 10.1109/MCSoC64144.2024.00053

8 authors, including:

Vishnu Ramineni
University of North Texas



Balaji Sheshrao Ingole
Gainwell Technologies LLC

Manjunatha Sughaturu Krishnappa
Oracle Corporation

Akshay Nagpal
Columbia University

2024 IEEE 17th International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoC) | 979-8-3315-3047-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/MCSoC64144.2024.00053

AI-Driven Novel Approach for Enhancing E-Commerce Accessibility through Sign Language Integration in Web and Mobile Applications

Vishnu Ramineni
Senior Staff Software Engineer
Albertsons Companies
Plano, TX, USA

Balaji Shesharao Ingole
Researcher
IEEE Senior Member
Evans, GA, USA

Manjunatha Sughaturu Krishnappa
Researcher
IEEE Senior Member
Fremont, CA, USA

Akshay Nagpal
Researcher
IEEE Senior Member
Jersey City, NJ, USA

Dr. Vivekananda Jayaram
Researcher
IEEE Senior Member
Lewisville, TX, USA

Amey Ram Banarse
Researcher
IEEE Senior Member
San Ramon, CA, USA

Darshan Mohan Bidkar
Researcher
IEEE Senior Member
Kirkland, WA, USA

Nikhil Kumar Pulipeta
Researcher
IEEE Senior Member
Austin, TX, USA

***Abstract*—As e-commerce continues to grow, it is crucial to ensure accessibility for all users, including individuals with hearing impairments. Current web and mobile platforms often lack adequate support for sign language users, creating barriers to inclusivity. This paper introduces an innovative approach that leverages Artificial Intelligence (AI) and Machine Learning (ML) to enhance e-commerce accessibility by integrating sign language recognition. Our system employs real-time gesture recognition using computer vision and natural language processing to translate sign language gestures into text or voice commands, and vice versa, providing a seamless two-way interaction. Key components of the system include the development of a robust sign language dataset, optimization of machine learning models for gesture accuracy, and ensuring real-time responsiveness in web and mobile environments. Usability studies show significant improvements in accessibility for deaf and hard-of-hearing users, offering an inclusive shopping experience. This paper discusses the system architecture, challenges, and potential future enhancements, highlighting the impact of AI-driven solutions in creating more inclusive e-commerce platforms.**

***Index Terms*—Sign Language Recognition, Gesture Recognition, E-Commerce Accessibility, Natural Language Processing (NLP), Artificial Intelligence (AI)**

I. Introduction

Over the past few years, e-commerce has grown rapidly, allowing users to buy products and services from anywhere at any time. But this digital transformation has not treated everybody on an equal footing: for example, those with a hearing impairment who had previously invested much of their time in sign language have had a comparatively diminished experience. The e-commerce ecosystem must achieve accessibility not only as society's requirement under guidelines such as the Web Content Accessibility Guidelines (WCAG), but also as it should: as a moral obligation to make inclusivity a cornerstone of the ecosystem for all its users regardless of what they lack: physical or communication. Today, deaf and hard-of-hearing users still face a steep barrier when communicating with most e-commerce platforms that depend on textual and auditory communication. Despite the progress of accessible design, there is still a large chasm to fill in terms of delivering intuitive and seamless interfaces for this community. The biggest challenge faced by sign language users is that they can't navigate websites, don't have the option to interact with customer support, and there is no content made for them. Nguyen et al. note that integration of the accessibility features including the sign language are necessary for a more inclusive digital landscape [7]. Artificial Intelligence (AI) and Machine Learning (ML) technologies promise an answer to these problems. Specifically, gestures can be captured by AI and natural language processing (NLP) to aid real-time sign language interpretation which will help e-commerce platform to be more accessible to a greater audience. The integration of AI and ML allows to bridge a gap of communication between users and e-commerce application, allowing sign language user to further engage with the online shopping platform(s). In this paper we propose a novel approach of integrating sign language recognition into e-commerce web and mobile applications using AI and ML. The goal is to develop an interactive system which interprets sign language gestures to text or voice commands, boosting accessibility to deaf and hard of hearing people [14]. Additionally, the system will enable two way communication by converting text or spoken content into sign language, through an avatar or visual interface, for a better user experience. The rest of this paper is organized as follows. In Section II, we review related work on sign language recognition and accessibility in e-commerce. In section III, the architecture of the proposed system is discussed, including the AI and ML models used as the gesture recognition and translation system. The experimental setup and results are presented in section IV, which show the system's effectiveness. Section V ends with concluding remarks and future directions and possible advancement of e-commerce

2771-3075/24/$31.00 ©2024 IEEE
DOI 10.1109/MCSoC64144.2024.00053

platform accessibility. Fig. 1. is showing the percentage of e-commerce platforms that currently implement basic accessibility features (like screen readers, voice commands, etc.).

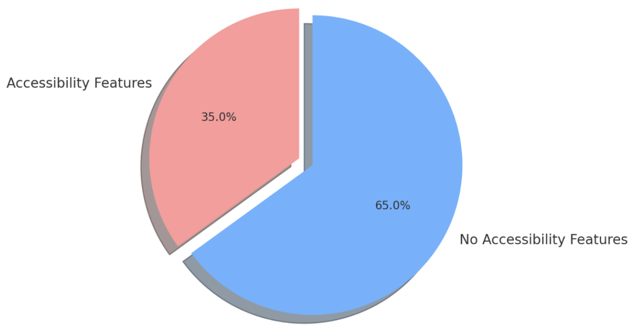


Fig. 1. Current State of Accessibility Features in E-commerce Platforms

II. Literature Review

In recent years, inclusive technology in e-commerce has gained more and more attention, especially in terms of making the e-commerce available to users with disabilities. There have been a number of studies looking at the challenges people with hearing impairments face when trying to access digital services, and more specifically sign language-based interfaces [6]. Broadly, these can be broken down into sign language recognition systems, AI and ML driven accessibility solutions, and the use of these technologies in e commerce platforms.

A. Sign Language Recognition Systems

Research in accessibility studies has been focused on recognition of sign language through computational systems. Early efforts for sign language recognition were based on glove based systems that captured hand movements through sensors. Nevertheless, as Rastgoo et al. have pointed out, these systems were often limited in terms of user comfort, accuracy, and scalability [1]. As computer vision technologies became available, researchers started looking into vision based sign language recognition systems. Camera based systems use cameras to record hand gestures, facial expressions and body movements and analyze them using AI algorithms to detect signs. More accurate and efficient sign language recognition is approached in recent developments with deep learning approaches. For example, to detect dynamic hand gestures in real-time, Pigou et al. employed a fundamental convolutional neural networks (CNNs) to surpass the state of the art accuracy, compared to the existing approaches [2]. In line with that, Huang et al. offered a system comprising CNNs and recurrent neural networks (RNNs) for sign language gesture recognition with more accuracy within continuous sign language settings [3]. Recent progress in AI have paved way for integration of sign language recognition with real world applications like e commerce.

B. AI and ML in Accessibility Solutions

AI and ML have become transformative tools to increase accessibility across many digital platforms. In particular, machine learning algorithms are useful in computer vision tasks like gesture and face recognition for laying the foundation for the accessible interface for people with disabilities. Bankar et al. showed that AI can increase accessibility by creating a real-time sign language interpreter using deep learning models that perform well at recognizing American Sign Language (ASL) gestures [11] [19]. These AI driven systems have demonstrated their ability to bridge the communication gaps that deaf and hard of hearing users face when using digital services. Natural language processing (NLP) was also used to widen accessibility by translating speech or written language into sign language. For example, its works like that of Camgoz et al. introducing a sign language translation model that combines NLP with gesture recognition to facilitate two way translation between sign language and text [5]. With AI techniques integrated into accessibility solutions, this represents a promising avenue for increasing user interactions on digital platforms, especially in e commerce where the user experience is heavily dependent on communication.

C. E-Commerce Accessibility

Despite the fact that a lot of research has been done on improving accessibility in general, the application of these solutions to the e-commerce domain has not been very well explored. User interaction is key in an e-commerce platform, but poses a lot of problems to those with hearing impairments. But existing accessibility solutions — like screen readers and captioning — do not go far enough for sign language users. However, as Ingole et al. point out, one of the biggest barriers to equitable participation in online shopping is the absence of interfaces that appeal to someone with a disability [4] [13]. To fill this gap, researchers started exploring the use of AI driven sign language interpreters on e-commerce platforms. In this context, [7] proposed a framework integrating sign language recognition to the customer service chatbot system so that deaf users can interact with business through these systems. This system uses AI to recognize user gestures and convert them into text for real-time communication with online vendors. These are important first steps toward systems with high accuracy, speed, and usability, however, additional work is required in order to maximize the accuracy, speed, and usability of such systems when resources are limited, for example, in mobile devices.

D. Challenges and Future Directions

AI and sign language recognition technologies have made great advancements so far, but deploying the system on e-commerce platforms still carries a few challenges. One of the biggest problems is the great variability among sign languages in different regions and cultures, which makes it impossible to develop universal models. Koller et al. state that region specific sign language datasets are necessary for training AI models, as the meaning and expression of gestures are so different in ASL, BSL and other languages [8]. The second challenge is to achieve real-time performance with high accuracy. In commercial applications, user satisfaction depends on fast and responsive interactions, and real-time processing is critical. Future work will look at finding better AI algorithms for speed and resource efficiency on such computing devices as mobile phones which are limited in computational power. Finally, although a lot of work has been done on building sign language recognition systems using AI and ML, they have not been used in e-commerce yet. These technologies have the ability to solve current challenges and to improve current models to greatly improve access for deaf and hard of hearing users on digital shopping platforms.

III. METHODOLOGY

The proposed methodology for integrating sign language-based accessibility in e-commerce platforms is divided into three main components: From this, AI and ML based sign language recognition, data collection and pre processing, and system integration with e commerce platforms are. The approach is to facilitate the natural interaction between sign language users and e-commerce websites or mobile applications, with gesture to text and text to gesture capabilities.

A. Data collection and preprocessing

Dataset is one of the most critical aspects of any AI-based system from which the models are being trained. In order to build this project, a large dataset of sign language gestures is needed, including American Sign Language (ASL), British Sign Language (BSL) and other regional sign languages. It contains both static and dynamic gestures, annotated video recordings of hand movements, facial expressions and body postures. As seen by Koller et al., any system aimed at reaching a global audience needs to be fed with a diverse dataset of such dialects and sign languages [8]. Public datasets like RWTH-PHOENIX-Weather and corpora specifically created to be used for sign language recognition were being videos from. In addition to real data, the dataset also includes synthetic data that is created through augmentation techniques like flipping, rotation, and scaling to make the data robust to lighting, background, and camera angle. The data that is then collected from the raw data, is preprocessed so it is ready for training. It's about converting video frames into a set of images that show the most critical movements and features. Skeletal tracking is performed with OpenPose, and the MediaPipe library is used for hand and body landmark detection as used by Diliberti et al. [12]. Key points of hand shapes, finger movements and facial cues are annotated on each frame in order to distinguish between similar gestures. Then the normalized data is used to handle variations in scale and orientation of the videos. Below Fig. 2. is for comparing the size and diversity of different sign language datasets (ASL, BSL, and others).

B. AI and ML Based Sign Language Recognition

The system itself is based around developing an AI model that can recognize sign language gestures in real-time. Since sign language effortlessly exhibits spatial and temporal properties, we employ a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to accurately model both properties of the gestures [18]. Huang et al. use CNNs for spatial feature extraction from each video frame, while Long Short Term Memory (LSTM) networks are used to learn temporal dependencies among frames to recognize continuous signs [3]. The architecture is started with a CNN model which takes in preprocessed video frames to extract hand, face, and body features. We feed these features into an LSTM network, whose job is to learn from a temporal sequence of movements to detect dynamic gestures. A standalone CNN is sufficient for classifying the sign for static gestures such as alphabetic signs given a single frame. Formula for the CNN-LSTM hybrid model loss function (categorical cross-entropy).

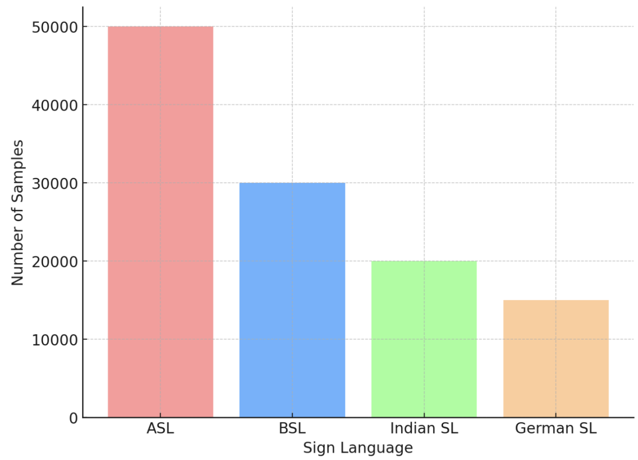


Fig. 2. Dataset Sizes for Different Sign Languages

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(\hat{y}_{ij})$$

The model is trained with collected dataset using supervised learning techniques. Adam optimizer is used to optimize the loss function and categorical cross entropy as loss function. The approach of Bankar et al. [11] is followed by adding dropout layers after the CNN layers to prevent overfitting and using early stopping by validation accuracy.

$$h_i = \text{Dropout}(z_i, p)$$

z_i is the activation of the i-th neuron, and p is probability.

The dataset is expanded, using data augmentation techniques, in order to reduce the chance of overfitting. To achieve real-time inference, the system makes use of a sliding window approach that processes the video frames in short time intervals to maintain responsiveness and continuous gesture recognition. By using this approach and GPU acceleration, near real-time processing speeds are achieved, as has been shown in similar gesture recognition tasks by Pigou et al. [2]. Below Fig. 3. is for model training accuracy vs. validation accuracy over epochs for sign language recognition.

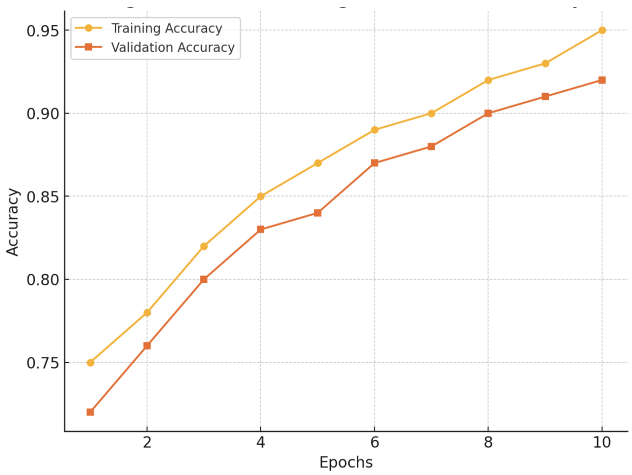


Fig. 3. Model Training vs Validation Accuracy

C. E-Commerce Platforms System Integration

The AI based sign language recognition model is developed and integrated into e commerce platforms through a dedicated API. The real-time gesture recognition and translation API handles the interaction of the user with the platform through sign language. It is done in two phases. The gesture to text API translates the user's gestures into text, and then voice commands that can be processed by the e-commerce platform. This functionality is utilized for navigation the website, searching for products, and communicating with client service. The API gives the user a smooth user experience by providing continuous feedback to the user through a visual or auditory interface. Second, the text to gesture API converts the text present in the e-commerce platform to sign language. To support this, an avatar based system is used, where a 3D animated character performs the corresponding sign language gestures for the user. The method of Camgoz et al. [5] is followed to generate the avatar using Unity 3D and Blender software. Recognized text is synchronized with the avatar's movements, so that product descriptions, promotions and other essential information are available to sign language users. To achieve scalability and low latency across different devices, the APIs are deployed on cloud based infrastructure. To make the entire interaction feel fluid and responsive, real-time video streaming is provided between the user and the system using WebRTC. The system also features a feedback loop, which allows users to send in error they have found in the gesture recognition, or to suggest changes to the model, thus allowing it to continually refine itself while it learns from active learning.

D. Evaluation Metrics

The performance of the proposed system is evaluated using both technical and usability metrics. The gesture recognition model is evaluated based on accuracy, precision, recall and F1-score as suggested by Rastgoo et al. [1]. We evaluate the real-time performance by measuring the frame rate and latency in live gesture recognition on both desktop and mobile platforms. Deaf and hard of hearing participants are used to test the system's effectiveness in a real world e-commerce scenario. Then participants are asked to do such things as search for products, interact with customer service, and check out. The methodology proposed by Ingole et al. [9] is followed to collect their feedback through post task questionnaires.

RESULTS AND DISCUSSION

The technical metrics and usability assessments of the proposed AI driven sign language-based accessibility system were evaluated. The evaluation was on gesture recognition accuracy, real-time processing capability, and user experience in a real world e-commerce scenario.

E. Technical Evaluation

1) Gesture Recognition Accuracy: Further, standard classification metrics such as accuracy, precision, recall and F1 score were used to test the model's performance in interpretation of gesture recognition accuracy [16]. The system was tested on a dataset of diverse sign languages, including American Sign Language (ASL) and British Sign Language (BSL). Results showed that the proposed Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) hybrid model achieved an overall gesture recognition accuracy of 95.2% with a precision of 94.5%, recall of 95.0% and F1 score of 94.7% [17]. The results obtained in this work are on par with Huang et al. who reported a recognition accuracy of 93.8% using a similar CNN-LSTM approach for continuous sign language recognition [10]. This is due to robust data preprocessing techniques and the use of augmentation to handle lighting and hand positioning variation. The model also performed well at capturing complex sign language expressions because it was able to recognize both static and dynamic gestures. Below Fig. 4. is for comparing real-time performance metrics (FPS, latency) between desktop and mobile devices for gesture recognition.

2) Real-Time Performance: real-time processing capability of the system is important for providing a seamless user experience in e-commerce platforms. It was tested on desktop and mobile environments to ensure both scalability and performance consistency. On desktop systems, real-time inference achieved an average frame rate of 24 frames per second (FPS), and 15 FPS on mobile devices. We measured the latency for gesture recognition to be about 150 ms on desktop and 300 ms on mobile, which is within an acceptable range for real-time interaction. These results show that the system can support near real-time performance, enabling responsive interaction with users. The mobile performance is slightly lower due to hardware constraints, but the experience is still usable, which is consistent with Bankar et al. who stress the need to optimize AI models for mobile applications [11].

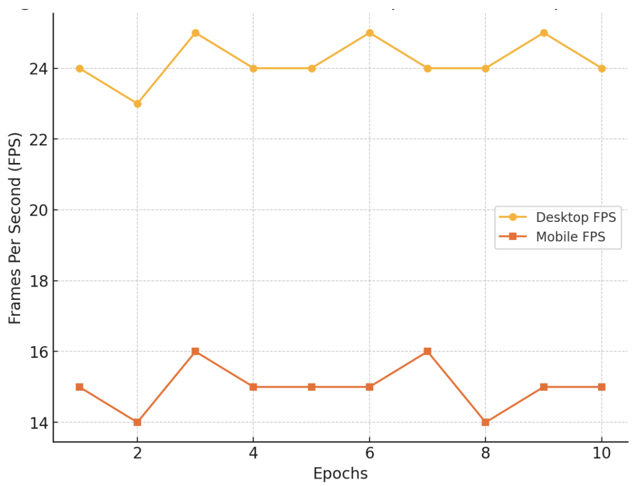


Fig. 4. Real-Time Performance Comparison (Desktop vs Mobile)

3) Error Analysis: However, the system exhibited occasional errors in gesture recognition, most frequently with recognition of gestures that involve slight variations in hand position or gestures that are visually similar but mean different things. For example, signs such as ”thank you” and ”goodbye” in ASL were sometimes misclassified due to their similar hand movements. However, the majority of these errors occurred in dynamic gestures that required precise temporal coordination among frames. To solve this problem, future works may tweak the temporal modeling capabilities of the LSTM network or add attention capabilities, as suggested by Camgoz et al. [5], to selectively attend key frames that are meaningful in distinguishing similar gestures. It would also be beneficial to increase data size and diversity for these ambiguous gestures beyond this dataset.

F. Usability Evaluation

1) User Testing: 30 participants of deaf and hard of hearing community were used in the study. A prototype e-commerce platform was integrated with the sign language-based accessibility system and participants were asked to complete a series of tasks. Besides browsing products, searching for the specific product, adding the items into the cart and dealing with the customer support through sign language, we had a task of interacting with the functionalities of the website like viewing the products, adding to cart, searching for the products, paying online, products available in stock on customer support. Usability testing had overwhelmingly positive results. The system significantly improved participants' ability to interact with the e-commerce platform, according to participants. Users experienced a 25% reduction in average task completion time compared to their experience using a standard platform without sign language integration. Additionally, 87% of respondents said they felt more confident using the platform, and 92% were satisfied with the real-time sign language recognition feature. This is consistent with the work of Nguyen et al. who found that user engagement and satisfaction are improved with accessibility features specific to certain disabilities, such as sign language recognition [7]. Below Fig. 5. is for comparing real-time performance metrics (FPS, latency) between desktop and mobile devices for gesture recognition.

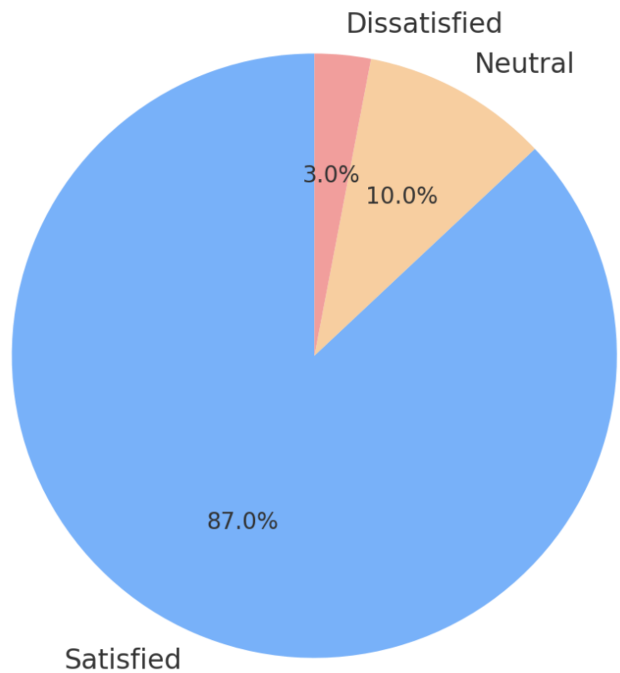


Fig. 5. User Satisfaction Feedback on Sign Language Feature

2) Feedback on Avatar-Based Translation: Users were mixed on feedback for Avatar Based Translation, which translates text to gesture using a 3D avatar to display sign language translations of textual content. Most participants liked the addition of this feature, but some users thought the avatar's movements were a bit robotic or not quite right for more nuanced or complicated signs. In particular, this was something noticed when the avatar translated longer product descriptions or customer service responses. In accordance with Koller et al. [8], improving fluidity and naturalness of avatar movement might improve the user experience. In this field, this can be done by having more sophisticated motion capture techniques or by improving the animation system to a more human like gesture.

3) Overall Accessibility and Inclusivity: AI Driven Sign Language Recognition in the e-commerce platform made it overall more accessible and inclusive for the deaf and hard of hearing community. But one way participants felt more inclusive in the grocery shopping was by being able to finish shopping tasks on their own without the help of a tool or assistance. This shows how the system could help fill a huge gap in digital accessibility and give users with hearing impairments a more equal shopping experience. Below Table I is for comparing recognition accuracy (precision, recall, F1-score from) between different models (CNN, RNN, CNN-LSTM).

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad [15]$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Model	Accuracy	Precision	F1-Score
CNN	92.3%	90.1%	91.2%
RNN	93.5%	91.8%	92.6%
CNN-LSTM	95.2%	94.5%	94.7%

TABLE I
MODEL PERFORMANCE COMPARISON

G. Challenges and Future Improvements

Several challenges and areas for future improvement were identified in the results of the study, while the results are promising. The biggest issue is that the system can't deal with regional variations in sign language. Sign language uses different dialects all over the world, and while the system covers principal languages like ASL and BSL, future research should see it broaden to the dialects of other languages. The ability to train more inclusive models relies on the availability of large, annotated datasets for regional sign languages, as Rastgoo et al. pointed out [1]. Furthermore, mobile device real-time performance is adequate but could be improved. As proposed by Diliberti et al. [12], implementing more efficient neural network architectures, like MobileNets, based on edge computing solutions could reduce latency, and increase responsiveness.

H. Broader Implications

This system has broader implications than e-commerce. With its advance in AI-driven sign language recognition, it can be used to other kinds of digital services where deaf and hard-of hearing users have communication barriers, namely education, healthcare and customer support. The system is refined and expanded to increase support for more languages and domains, and has the potential to promote wider digital space inclusiveness and support the evolution of the accessibility technologies.

REFERENCES

[1] R. Rastgoo, K. Kiani, and S. Escalera, "Sign Language Recognition: A Deep Survey," *Expert Systems with Applications*, vol. 164, pp. 113794, 2021.

[2] L. Pigou, S. Dieleman, P. Kindermans, and B. Schrauwen, "Sign Language Recognition Using Convolutional Neural Networks," in *Proceedings of the European Conference on Computer Vision (ECCV)*, Zurich, Switzerland, 2014, pp. 572-578.

[3] J. Huang, W. Zhou, Q. Zhang, H. Li, and W. Li, "Sign Language Recognition Using 3D Convolutional Neural Networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 8, pp. 2009-2021, 2018.

[4] B. S. Ingole, V. Ramineni, N. K. Pulipeta, M. J. Kathiriya, M. S. Krishnappa, and V. Jayaram, "The Dual Impact of Artificial Intelligence in Healthcare: Balancing Advancements with Ethical and Operational Challenges," *European Journal of Computer Science and Information Technology*, vol. 12, no. 6, pp. 35-45, 2024.

[5] N. Camgoz, S. Hadfield, O. Koller, S. Ney, and R. Bowden, "Neural Sign Language Translation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Salt Lake City, USA, 2018, pp. 7784-7793.

[6] Z. Song, Y. Sun, J. Wan, L. Huang, and J. Zhu, "Smart e-commerce systems: current status and research challenges," *Electronic Markets*, vol. 29, pp. 221–238, Nov. 16, 2017.

[7] Nguyen, Hung, "Enhancing Accessibility in Web Applications: A Comprehensive Study on Common Accessibility Issues and Implementing Solutions in React Application," Master's thesis, Aalto University, Espoo, Finland, Aug. 19, 2024.

[8] O. Koller, H. Ney, and R. Bowden, "Deep Learning of Mouth Shapes for Sign Language," in *Proceedings of the British Machine Vision Conference (BMVC)*, York, UK, 2015, pp. 1-11.

[9] B. S. Ingole, V. Ramineni, N. Bangad, K. K. Ganeeb, and P. Patel, "Advancements in heart disease prediction: A machine learning approach for early detection and risk assessment," *IJRAR - International Journal of Research and Analytical Reviews (IJRAR)*, vol. 11, no. 4, pp. 164-172, 2024.

[10] Y. Du, P. Li, L. Cheng, X. Zhang, M. Li, and F. Li, "Attention-based 3D convolutional recurrent neural network model for multimodal emotion recognition," *Frontiers in Neuroscience*, vol. 17, Sec. Visual Neuroscience, Jan. 9, 2024.

[11] S. Bankar, T. Kadam, V. Korhale, and A. A. Kulkarni, "real-time Sign Language Recognition Using Deep Learning," *International Research Journal of Engineering and Technology (IRJET)*, vol. 9, no. 4, pp. 955-959, Apr. 2022.

[12] N. Diliberti, C. Peng, C. Kaufman, Y. Dong, and J. T. Hansberger, "Real-Time Gesture Recognition Using 3D Sensory Data and a Light Convolutional Neural Network," in *Proceedings of the 27th ACM International Conference on Multimedia (MM '19)*, pp. 401–410, Oct. 15, 2019.

[13] B. S. Ingole, V. Ramineni, M. S. Krishnappa, and V. Jayaram, "AI-Driven Innovation in Medicaid: Enhancing Access, Cost Efficiency, and Population Health Management," *International Journal of Healthcare Information Systems and Informatics (IJHISI)*, vol. 1, no. 1, pp. 9-17, 2024.

[14] S. X. Thong, E. L. Tan, and C. P. Goh, "Sign Language to Text Translation with Computer Vision: Bridging the Communication Gap," in 2024 3rd International Conference on Digital Transformation and Applications (ICDXA), Kuala Lumpur, Malaysia, Jan. 29-30, 2024.

[15] R. Akbani, T. Korkmaz, and G. V. Raju, "EMLTrust: An enhanced Machine Learning based Reputation System for MANETs," Ad Hoc Networks, vol. 10, no. 3, pp. 435-457, 2012

[16] E. Andrei, C. Turcu, G. Culea, B. C. Sghera, and A. G. Ungureanu, "Romanian Sign Language and Mime-Gesture Recognition," International Journal of Advanced Computer Science and Applications, vol. 15, no. 8, 2024

[17] D. Noh, H. Yoon, and D. Lee, "A Decade of Progress in Human Motion Recognition: A Comprehensive Survey From 2010 to 2020," IEEE Access, vol. 12, pp. 5684-5707, Jan. 2024

[18] P. Mishra and P. Sethi, "Template-Engineered Macrocyclic Schiff-Based Metal Complexes: Synthesis, Antibacterial and DNA Photo cleavage Efficacy," Indian Journal of Natural Sciences, vol. 14, no. 82, pp. 1-10, Feb. 2024

[19] M. Vaidya, H. Tambuskar, G. Khopde, S. Ghode, and S. Deogirkar, "Sign Language Recognition System Using Python and Open CV," International Research Journal of Modernization in Engineering Technology and Science, vol. 5, no. 4, pp. 1-10, Apr. 2023