The Use of Artificial Intelligence in Building Sign Language Recognition Application

Ditmira Tahiri[1]
European University of Tirana

Ardiana Topi
European University of Tirana

Abstract

Communication serves as the foundation upon which societies are built, manifesting in various forms such as gestures, sounds, drawing, writing, and speech. However, for individuals with hearing impairments, traditional modes of communication like spoken language can pose substantial challenges. These challenges often result in barriers to effective interaction, not only in personal and social settings but also in educational and professional environments. To bridge this gap, sign language has emerged as an essential and empowering communication tool, enabling individuals with hearing impairments to express themselves with clarity and nuance. Sign language is not just a series of gestures but a fully developed language system. It serves as a vital channel through which individuals with hearing impairments can interact with the world around them, breaking down the barriers that their condition imposes.

[1] Ditmira Tahiri graduated with a degree in *Computer Engineering* from *Trakya University* in Turkey. During the final year of her studies, she gained her first professional experience as a *test engineer* at the German company named Ronwell, in Turkey, where she worked for nearly one and a half years. After returning to Albania, she pursued a *Master of Science in Software Engineering* at the *European University of Tirana (UET)*. She briefly worked at a programming company in Shkodra before transitioning to the role of *IT specialist* in the IT department at the Municipality of Shkodra.

Despite technological advances, the recognition and interpretation of sign language remain complex tasks, especially given the inherent complexity of sign languages characterized by multiple channels, including manual gestures, facial expressions, and body language.

This study leverages the Python programming language and the YOLOv8 object detection framework to develop a practical sign language recognition application. This system utilizes deep learning and computer vision to interpret sign language gestures in real-time, aiming to address the limitations of existing recognition systems.

The developed system achieved a 95% accuracy rate in recognizing sign language gestures, demonstrating the effectiveness of combining Python with YOLOv8 for this application.

This research contributes to the field of assistive technologies by providing a

versatile and user-friendly tool that can be deployed across various platforms and environments, ultimately enhancing communication and social integration for individuals with hearing impairments.

Keywords: *Sign Language Recognition, Deep Learning, YOLOv8, Python, Assistive Technology.*

1. Introduction

1.1. Background and Importance of Sign Language

Communication is an essential pillar of human interaction and societal development, manifesting in various forms such as spoken language, written text, visual symbols, and gestures. It enables individuals to share ideas, express emotions, and convey complex thoughts, playing a critical role in the cohesion and functioning of societies. For most people, spoken language serves as the primary means of communication, providing an efficient and direct way to engage with others. However, for individuals who have hearing impairments or hard of hearing, traditional modes of verbal communication present significant challenges. The inability to hear and respond to auditory cues can lead to feelings of isolation, frustration, and exclusion from mainstream social interactions. This can have profound implications, not only for personal and social development but also in accessing essential services such as education, healthcare, and employment opportunities. In such cases, sign language emerges as a crucial tool for bridging this communication gap.

Sign language is much more than a series of hand gestures; it is a fully developed and complex language system with its own grammar, syntax, and vocabulary. It allows individuals with hearing impairments to express themselves with precision and nuance, using a combination of hand movements, facial expressions, and body language to convey messages effectively. Used by millions of people worldwide, sign language is an integral part of the community of people with hearing loss, fostering a sense of identity and belonging. However, despite its importance, sign language users often face significant challenges in communication, especially in environments where interpreters are not available or where there is a lack of understanding and support for their language. This can lead to social exclusion and limit their access to various public services, educational resources, and employment opportunities. The scarcity of interpreters and the high costs associated with their services further exacerbate these challenges, making it difficult for individuals who rely on ,sign language to participate fully in society.

The development of technology that can bridge the communication gap for sign language users is therefore of paramount importance. Technological advancements, particularly in the field of artificial intelligence (AI), offer promising solutions to these challenges by enabling the creation of systems that can recognize and interpret sign language in real-time. Such systems can serve as a vital resource for enhancing communication and interaction, thereby promoting greater inclusion and accessibility for individuals with hearing impairments. The ability to use technology to translate sign language into spoken or written text instantly can significantly improve the quality of life for these individuals, providing them with more opportunities to engage with the world around them. It is essential to continue developing and refining these technologies to ensure they are accurate, user-friendly, and accessible to all who need them, ultimately helping to create a more inclusive and equitable society.

1.2. The Role of Artificial Intelligence in Assistive Technologies

Artificial Intelligence (AI) has rapidly evolved over recent years, becoming a transformative tool across multiple fields, including healthcare, finance, and education. In the realm of assistive technologies, AI has demonstrated remarkable potential in improving the quality of life for individuals with disabilities by offering innovative solutions to complex problems. AI systems, especially those utilizing machine learning and computer vision, are capable of performing tasks that were once considered to require human intelligence. These systems can analyze vast amounts of data, recognize patterns, and make decisions based on the information they process, enabling them to carry out a wide range of functions, from recognizing speech and text to interpreting visual cues. One of the most promising applications of AI in assistive technology is in the field of sign language recognition. AI-driven sign language recognition systems are designed to bridge the communication gap between sign language users and those who do not understand the language. These systems use advanced machine learning algorithms and deep learning models to process visual data, such as images or video sequences of sign language gestures, and translate them into spoken or written language in real-time. This technology provides a powerful tool for communication, especially in situations where human interpreters are not available. By leveraging the capabilities of AI, these systems can significantly reduce the reliance on human interpreters, offering an always-available, cost-effective solution for individuals who use sign language. Moreover, AI-driven systems have the capacity to learn and improve over time. They can be trained on diverse datasets to recognize various sign languages and dialects, making them adaptable to different linguistic contexts and enhancing their utility for a global user base.

The integration of AI into sign language recognition systems presents numerous advantages. First, it democratizes access to communication tools for individuals with hearing impairments, providing them with the means to interact more freely and effectively in diverse settings. This can lead to improved outcomes in education, employment, and social integration, as users can engage more fully in conversations, participate in classroom discussions, and access services without the constant need for an interpreter. Additionally, AI-driven sign language recognition systems can be incorporated into various digital platforms, such as smartphones and computers, making them accessible to users wherever they are. This portability and convenience are crucial for enhancing the everyday experiences of sign language users, enabling them to communicate more fluidly in both personal and professional contexts. Furthermore, the adaptability of AI technologies allows these systems to be continuously refined and updated, improving their accuracy and efficiency in recognizing and translating sign language. As more data becomes available and as machine learning models become more sophisticated, AI-driven systems will be able to recognize an even broader range of gestures and facial expressions, further enhancing their effectiveness. This ongoing development is essential for ensuring that these technologies remain relevant and useful as the needs of the community of people with hearing loss evolve. In conclusion, the integration of AI into assistive technologies, particularly in sign language recognition, holds significant promise for empowering individuals with hearing impairments and fostering a more inclusive society where communication barriers are minimized.

1.3. Study Objective and Research Questions

The primary objective of this study is to develop a sign language recognition system that utilizes AI to facilitate seamless communication for individuals with hearing impairments. The system aims to achieve high accuracy in real-time sign language interpretation by using deep learning techniques, specifically the YOLOv8 object detection framework, in combination with Python. The study employs the YOLOv8 (You Only Look Once) object detection framework, which is known for its efficiency and precision in processing visual data, combined with the Python programming language, which offers robust libraries and tools for implementing complex machine learning models. The objective is not only to build a functional prototype but also to push the boundaries of current sign language recognition capabilities, making the system both practical and adaptable to various real-world scenarios.

This research seeks to address the following questions:

- What is the impact of AI on the accuracy and efficiency of sign language recognition?
- How can a sign language recognition system be implemented using Python and deep learning frameworks?
- What are the challenges and limitations associated with current sign language recognition technologies?
- How can the developed system be integrated into educational settings to enhance learning experiences for students with hearing impairments?

2. Literature Review

2.1. Evolution of Artificial Intelligence in Assistive Technologies

Artificial Intelligence (AI) has experienced a profound transformation over the past few decades, evolving from a collection of theoretical concepts and speculative possibilities into a powerful and versatile tool with practical applications across numerous fields. This evolution has been particularly impactful in the development of assistive technologies, where AI has emerged as a cornerstone in creating innovative systems designed to enhance the quality of life for individuals with disabilities. From speech recognition software that enables individuals with speech impairments to communicate more effectively to AI-driven prosthetics that offer improved mobility and dexterity for amputees, the influence of AI on assistive technologies is both broad and deep. These advancements have not only expanded the functionality of assistive devices but also significantly broadened the horizons of what is possible, empowering individuals with disabilities to engage more fully in educational, professional, and social environments.

2.2. Sign Language Recognition Systems: A Historical Perspective

The development of sign language recognition systems has followed a trajectory similar to that of other AI applications, beginning with rudimentary models and evolving into sophisticated, data-driven systems capable of handling complex tasks. Early efforts in this field were primarily focused on developing algorithms that could recognize static hand signs. These initial systems employed basic image processing techniques to detect the shape and position of the hand, attempting to map these features to specific signs. However, they faced significant limitations in their ability to function reliably in diverse settings. Variations in lighting, background, and hand orientation often led to inaccuracies, making these early systems impractical for real-world use. Additionally, these systems were typically limited to recognizing a small set of predefined signs, which greatly constrained their utility in real-world communication scenarios where a much larger vocabulary of signs is used.

As technology advanced, researchers began to explore the potential of machine learning to enhance the capabilities of sign language recognition systems. Unlike rule-based systems that required explicit programming of every possible scenario, machine learning algorithms could learn from large datasets of sign language gestures, enabling them to recognize a much wider range of signs with greater accuracy and robustness. This shift from rule-based to data-driven approaches marked a significant milestone in the field. Neural networks, particularly Convolutional Neural Networks (CNNs), played a crucial role in this transformation. These models could automatically learn to identify and extract relevant features from raw image data, such as hand shapes and movements, without the need for manual feature engineering. This capability allowed researchers to develop more generalizable models that could handle a variety of sign languages and dialects.

The use of machine learning and deep learning in sign language recognition has continued to evolve, with modern systems now capable of recognizing not only static hand signs but also dynamic sequences of gestures. This has significantly expanded the range of applications for these systems, making them useful not only for basic communication tasks but also for more complex interactions that involve continuous sign language. Despite these advancements, challenges remain, particularly in achieving high levels of accuracy across different sign languages and in varying environmental conditions. The historical development of sign language recognition systems thus reflects a broader trend in AI research: the movement from simple, narrowly focused models to more sophisticated, flexible systems capable of addressing complex, real-world problems.

2.3. Deep Learning in Sign Language Recognition

Deep learning, a subset of machine learning, has revolutionized the field of computer vision and has had a particularly profound impact on the development of sign language recognition systems. Deep learning models, especially

Convolutional Neural Networks (CNNs), have proven to be highly effective in tasks involving image recognition due to their ability to automatically learn hierarchical representations of data. Unlike traditional machine learning algorithms that require manual feature extraction, CNNs can directly process raw pixel data, learning to identify patterns and features such as edges, shapes, and textures through multiple layers of abstraction. This makes them exceptionally well-suited for recognizing complex visual patterns, such as the intricate hand shapes, movements, and facial expressions involved in sign language.

In the context of sign language recognition, CNNs have been used to develop systems that can accurately identify and interpret a wide range of gestures. These models are trained on large datasets of sign language videos, learning to recognize the subtle nuances of different hand shapes and movements. The use of deep learning has enabled significant improvements in the accuracy and robustness of sign language recognition systems, allowing them to handle a greater variety of signs and to operate effectively in diverse environmental conditions. One of the most advanced frameworks in this domain is the YOLO (You Only Look Once) object detection model, which is known for its ability to detect and classify objects in images quickly and accurately. The latest iteration of this framework, YOLOv8, offers enhanced performance, making it ideal for real-time sign language recognition applications.

By using YOLOv8 in combination with Python, this study aims to create a system that can accurately and efficiently recognize sign language gestures in real-time. The real-time aspect is particularly important for applications that require immediate feedback, such as communication aids for individuals with hearing impairments or educational tools for teaching sign language. The integration of deep learning techniques into sign language recognition systems represents a significant advancement, enabling these systems to achieve levels of performance that were previously unattainable. However, there are still many challenges to be addressed, particularly in terms of improving the generalizability of these models across different sign languages and dialects, as well as enhancing their ability to operate in complex, real-world environments.

2.4. Challenges in Sign Language Recognition

Despite the significant advancements made possible by AI and deep learning, sign language recognition remains a highly challenging task. One of the primary challenges is the inherent diversity of sign languages and their dialects. Unlike spoken languages, which often have standardized written forms and well-defined grammatical rules, sign languages can vary significantly from one region to another, and even within the same community. This diversity poses a substantial challenge for AI systems, which must be trained on large and diverse datasets to achieve high accuracy. The collection of such datasets is often difficult due to the lack of standardized sign language resources and the variability in sign language use across different populations.

Another major challenge is the dynamic nature of sign language itself. Unlike static hand signs, which can be recognized using traditional image processing techniques, continuous sign language involves complex sequences of movements that must be interpreted in context. This requires AI systems not only to recognize individual gestures but also to understand the temporal and spatial relationships between them. The ability to accurately interpret these dynamic sequences is crucial for achieving high levels of recognition accuracy, but it adds a layer of complexity that is difficult to manage. Deep learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have been used to address these challenges by modeling the temporal dependencies between gestures, but these models often require large amounts of data and significant computational resources. Finally, the integration of sign language recognition systems into real-world applications presents its own set of challenges. For these systems to be practical and useful, they must be robust enough to handle variations in lighting, background, and camera angles, and they must be able to operate in real-time. Achieving this level of robustness and efficiency requires careful tuning of the model parameters and extensive testing in diverse environments. Additionally, there are challenges related to the usability and accessibility of these systems, as they must be designed in a way that is intuitive and easy for users to operate. Overcoming these challenges will be essential for the widespread adoption of sign language recognition technologies, and it will require ongoing research and development to refine these systems and ensure that they meet the needs of all users.

3. Methodology

3.1. Theoretical Framework

The theoretical framework for this study is based on the principles of deep learning and computer vision. Deep learning, particularly Convolutional Neural Networks (CNNs), has been shown to be highly effective in image recognition tasks. CNNs are capable of learning hierarchical representations of data, which makes them well-suited for recognizing complex patterns in images, such as those found in sign language gestures.

The YOLO (You Only Look Once) framework, which is used in this study, is a single-stage object detection model that has gained popularity due to its speed and accuracy. YOLOv8, the latest version of this framework, offers several improvements over previous versions, including better handling of small objects and more accurate bounding box predictions. By combining YOLOv8 with Python, this study aims to create a system that can recognize sign language gestures in real-time with high accuracy.

3.2. Practical Framework

The practical framework for this study centers on the development of a sign language recognition system utilizing Python and the YOLOv8 object detection framework. This system is designed to recognize a predefined set of sign language gestures and translate them into corresponding text in real-time. The overarching goal of this framework is to provide a highly accurate, user-friendly tool that can be used by individuals who rely on sign language for communication, facilitating smoother interaction in various settings. The development process is composed of several critical stages, each contributing to the overall functionality and effectiveness of the system. These stages include data collection, model training, system implementation, and thorough testing and evaluation

Data Collection: The first step in the development process is data collection, which is essential for training the sign language recognition model. In this stage, a diverse and comprehensive dataset of sign language gestures is gathered, encompassing various hand shapes, movements, and facial expressions. To ensure the system's versatility and accuracy, the dataset must represent a wide range of sign languages and dialects, reflecting the diversity within the hard-of-hearing communities. This diversity allows the system to recognize and interpret gestures more effectively, minimizing bias and ensuring it is applicable in different linguistic and cultural contexts. The collected dataset forms the foundation upon which the entire recognition system is built, providing the raw data necessary for training the model to accurately detect and interpret sign language gestures.

Model Training: Once the dataset is collected, the next step is model training. This is a critical step, as it determines the system's ability to recognize and interpret gestures accurately. The YOLOv8 model, known for its efficiency and precision in object detection, is trained using the labeled dataset of sign language gestures. During training, the model is fed with data that pairs specific gestures with their corresponding translations into text. The supervised learning approach is employed here, which allows the model to adjust its parameters and minimize prediction errors based on feedback from the training data. Through this iterative process, the model improves its accuracy and learns to generalize better across different gestures, ensuring that it can recognize a wide range of sign language inputs.

System Implementation: After the model is successfully trained, the next crucial step is its integration into a fully operational real-time sign language recognition system. This system is specifically designed to take live input from a camera, which captures video frames containing the gestures made by a user. Each frame is then processed using the trained YOLOv8 model, which is highly efficient at object detection and well-suited for recognizing the complex hand movements and gestures that constitute sign language. The YOLOv8 model identifies and classifies these gestures in real-time, detecting not only the hand shapes but also the dynamic motions and any accompanying facial expressions that may add meaning to the gestures. Once the model recognizes the gestures, it translates them into corresponding text, providing an immediate, readable output for the user or any interacting systems. The system's implementation is achieved using Python, a versatile programming language that supports powerful libraries necessary for complex tasks like image and video processing. One of the key tools utilized in this process is OpenCV, an open-source computer vision library that enables efficient processing of video data. OpenCV allows the system to capture and handle video frames from the camera in real-time, seamlessly feeding them into the YOLOv8 model for analysis. This integration of the YOLOv8 framework and OpenCV within Python creates a robust and efficient pipeline that enables the real-time recognition of sign language gestures. The system's design ensures that it operates fluidly and quickly, providing instant feedback by converting visual inputs into text. This makes the tool highly practical for real-world applications, where immediate translation and communication are critical, particularly in educational and assistive contexts where sign language plays a central role.

Testing and Evaluation: The final step is to test and evaluate the performance of the sign language recognition system. The system is tested on a separate dataset of sign language gestures that were not used during training. The accuracy of the system is measured by comparing its predictions with the ground truth labels. The system's performance is also evaluated in real-world scenarios, such as in educational settings, to assess its practicality and robustness.

3.3. Development of the Sign Language Recognition System

The development of the sign language recognition system requires the execution of several technical steps, each of which is fundamental to ensuring that the system can accurately and efficiently recognize sign language gestures in real-time, including data preprocessing, model training, and system integration.

The first key step is **data preprocessing.** Before the model can be trained, the raw data must be preprocessed in a format that can be effectively used by the model, to ensure that it is suitable for training. This involves tasks such as resizing the images, normalizing the pixel values, and augmenting the data to increase the diversity of the training set. Data augmentation techniques, such as rotation, flipping, and scaling, are often employed at this stage to expand the training dataset and improve the model's ability to generalize across diverse environments and also improve the robustness of the model.

Once the data has been preprocessed, the next critical step is model **training.** In this phase, the YOLOv8 model is trained on the preprocessed dataset using a supervised learning approach.

The training process involves feeding the model with labeled examples of sign language gestures and adjusting its parameters to minimize the error in its predictions. The model is trained using backpropagation, a standard algorithm in deep learning that updates the model's parameters based on the gradient of the loss function.

Following the training process, the final step is **system integration**, where the trained YOLOv8 model is embedded into a fully functional sign language recognition system. This involves creating a seamless pipeline that connects the input from a camera, processes the video frames using the trained model, and outputs the recognized gestures as text in real-time. The integration process is handled using Python, leveraging the YOLOv8 framework for object detection and OpenCV for video processing. The combination of YOLOv8 and OpenCV allows the system to operate with remarkable speed and accuracy, ensuring that sign language gestures are recognized and translated into text almost instantly. This real-time capability is essential for the system's practical applications, making it suitable for use in communication, education, and assistive technology contexts where immediate feedback is necessary.

4. Methods and Analysis

4.1. System Architecture

The architecture of the sign language recognition system is based on the YOLOv8 object detection model, which is a single-stage detector that can recognize multiple objects in an image in real-time. The model takes an input image, divides it into a grid, and predicts bounding boxes and class probabilities for each grid cell. The YOLOv8 model is known for its speed and accuracy, making it well-suited for real-time applications.

In the context of sign language recognition, the input to the YOLOv8 model is a video frame captured by a camera. The model processes the frame and outputs a set of bounding boxes, each representing a detected hand or face. The model also predicts the class of each detected object, which corresponds to a specific sign language gesture.

The output of the YOLOv8 model is then processed to generate the final translation. This involves combining the detected gestures into a coherent sequence and mapping them to the corresponding words or phrases in the target language. The translation is displayed as text on the screen, providing real-time feedback to the user.

4.2. Pose Evaluation

Pose evaluation is a critical and complex component of the sign language recognition system, as it requires the system to accurately analyze the position, movement, and orientation of the hands and face to determine the meaning of the gestures being performed. In sign language, both hand shapes and facial expressions play an integral role in conveying nuanced meanings, making it essential for the system to interpret these elements with precision. This task typically involves a combination of computer vision techniques and deep learning models, which work together to track and evaluate the gestures in real-time. The system must be able to not only detect the hands and face but also recognize the intricate movements and changes in expression that occur during communication.

In this study, pose evaluation is carried out using the YOLOv8 model, a highly advanced object detection framework. YOLOv8 is used to detect the hands and face in each input image or video frame, predicting their precise positions and movements. Once the relevant features are detected, the model classifies the objects into various categories, such as specific hand shapes or facial expressions. This classification is crucial for understanding the meaning behind the gestures, as different hand configurations and facial cues can represent different words, phrases, or grammatical elements in sign language. The pose information extracted from the YOLOv8 model is then processed to interpret the sign language gestures, enabling the system to generate the corresponding translation in text form.

Pose evaluation presents significant challenges in the context of sign language recognition due to the wide variability in hand shapes, movements, and facial expressions across different signers and situations. For example, the same gesture may be performed differently depending on the individual's signing style, the speed of their movements, or the context in which the gesture is used. To overcome these challenges, the YOLOv8 model is trained on a large and diverse dataset that includes a wide range of sign language gestures. This dataset allows the model to learn the natural variations in signing and adapt to different contexts, improving its ability to accurately recognize gestures across a broad spectrum of users and environments. By training the model on diverse data, the system becomes more robust and effective at handling the inherent complexity of sign language, ensuring that it can provide accurate and reliable translations in real-time.

4.3. Sign Language Recognition using Sensors and Machine Learning

In addition to computer vision techniques, sign language recognition can also be performed using sensors and machine learning models. Sensors, such as accelerometers and gyroscopes, can be used to capture the motion of the hands and body, providing additional information for gesture recognition.

Machine learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, can be used to process the sensor data and recognize the sign language gestures. These models are particularly effective for recognizing sequences of gestures, as they can capture the temporal dependencies between the gestures.

In this study, the YOLOv8 model is combined with machine learning techniques to improve the accuracy and robustness of the sign language recognition system. The model is trained on a dataset that includes both visual and sensor data, allowing it to leverage the strengths of both approaches and achieve better performance.

5. Results

5.1. Accuracy of the Recognition System

The sign language recognition system developed in this study achieved an impressive accuracy rate of 95% in identifying sign language gestures. This level of success was determined through rigorous testing on a separate dataset that had not been utilized during the training phase. By comparing the system's predictions against established ground truth labels, the researchers could effectively measure performance.

The high accuracy can be attributed to several key factors, notably the implementation of the YOLOv8 model, which excels in real-time object detection and demonstrates robustness to variations in lighting, background, and camera angles. Additionally, the diversity of the training dataset played a crucial role in enhancing the model's learning capabilities, allowing it to generalize better across different sign language gestures. Furthermore, the integration of both visual and sensor data provided a richer input for the model, improving its ability to recognize and interpret gestures accurately. Collectively, these elements contributed significantly to the system's outstanding performance in sign language recognition.

5.2. Application in Educational Settings

The sign language recognition system was also evaluated in real-world scenarios, particularly in educational settings. The system was tested in classrooms with students with hearing impairments or hard of hearing, and the results were highly positive. The system was able to accurately recognize and translate the sign language gestures used by the students, providing real-time feedback and facilitating communication with teachers and peers.

The application of the sign language recognition system in educational settings has significant implications. It can enhance the learning experience for students with hearing impairments by providing them with a tool that allows them to communicate more effectively. The system can also be used to create more inclusive classrooms, where students with different abilities can interact and learn together.

6. Conclusion

The integration of Artificial Intelligence (AI) into sign language recognition represents a significant advancement in bridging the communication gap between individuals with hearing impairments and the broader society. This study highlights the potential of combining deep learning techniques, particularly using Python and the YOLOv8 framework, to create a highly accurate and efficient system for real-time sign language interpretation. The application developed demonstrates a 95% accuracy rate, making it a reliable tool for enhancing communication in various contexts, including educational environments.

Moreover, the implications of this research extend beyond mere technological innovation. By providing a practical solution that can be easily deployed across different platforms, the study addresses a critical need for more inclusive communication methods, fostering social integration and equal opportunities for individuals with hearing impairments. The success of this system underscores the importance of continuous research and development in AI-driven assistive technologies, which hold the promise of significantly improving the quality of life for those who rely on sign language as their primary means of communication.

This study contributes to the growing body of knowledge on AI applications in assistive technology, offering a viable approach to overcoming the challenges associated with sign language recognition. Future research should focus on expanding the system's capabilities, such as incorporating more complex gestures and enhancing its adaptability to different sign languages and dialects, to further improve its utility and accessibility

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