Roadmap for Advancing Tunisian Sign Language Recognition: Lessons Learned from Global Sign Language Systems

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***Abstract*—Automated systems that can recognize sign language are important tools for helping deaf people communicate with people who can hear them. Sign languages, such as American Sign Language, Chinese Sign Language, and Arabic Sign Language, have improved significantly in terms of accuracy and reliability owing to advancements in artificial intelligence, computer vision, and sensing technologies. These systems work better when they have access to large amounts of data, an evaluation benchmark, and the ability to use different types of sensors.**

Even with these changes, research on how to recognize Tunisian sign language is still in its early stages of technological maturity. Most modern systems depend on vision-based sensing and are typically tested in laboratories using small datasets. Owing to these factors, issues with robustness, scalability, and deployment in the real world still exist.

This study aims to identify critical areas for enhancement in Tunisian sign language recognition by examining technological trends and best practices evident in established sign language systems. This study analyzes the current condition of Tunisian sign language recognition, derives insights from international sign language research, and suggests prospective pathways for system advancement. Special attention is paid to the possible role of advanced sensing technologies, such as radar-based gesture recognition, which has great potential for use in low-light settings and situations in which privacy is important. The results provide a clear plan for improving the recognition of Tunisian sign language so that it can be used in real-life communication that is reliable and easy to access.

I. Introduction

Although recognition of Tunisian Sign Language exists, it is not as advanced as the systems used worldwide. Research on Tunisian sign language recognition is still in its early stages. This is because there are few datasets, sensing modalities, or standardized evaluation frameworks available. However, recognition systems designed for widely used sign languages have made significant progress owing to advanced sensing technologies, large datasets, and real-time deployment strategies [1], [2].

II. Comparative Analysis of Global Sign Language Recognition Systems

The comparative tables presented in this section summarize the main technological trends in global sign language recognition systems. The information was synthesized from recent survey and experimental studies published between 2022 and 2025, which analyzed sensing modalities, dataset characteristics, feature extraction methods, and machine learning models used in modern sign language recognition frameworks [1]–[4].

A. Sensing Modalities

Recent studies have demonstrated that the choice of sensing modality significantly influences the efficacy and reliability of sign language recognition systems. Vision-based systems remain the most prevalent owing to their user-friendliness and superior spatial resolution. Nonetheless, elements such as illumination and obstruction influence them [1], [5].

Depth sensors improve motion tracking accuracy by providing three-dimensional spatial information, whereas wearable sensors enable precise evaluation of finger movements, although they may compromise user comfort and natural interaction [2].

Additionally, radar-based sensing has emerged as an effective technology for gesture recognition, operating independently of lighting conditions and ensuring user privacy, thus making it suitable for practical use in low visibility environments [6], [7].

Multimodal sensing systems exhibit superior accuracy and reliability compared to single-sensor systems [3]. See Table I.

B. Dataset Characteristics Across Sign Languages

The characteristics of the dataset are essential for the efficacy and applicability of models that recognize sign language. Models are more stable and less likely to overfit when they have a large amount of data from many different people and recording settings [4].

Recent studies emphasize that publicly available datasets enhance reproducibility and benchmarking across diverse recog-

TABLE I

COMPARISON OF SENSORS USED FOR SIGN LANGUAGE RECOGNITION

Ref.	Sensor Type	Strengths	Limitations	Accuracy
[1]	Multimodal Sensors	High robustness and complementary features	Increased system complexity	N/A
[2]	RGB Camera	Low cost, real-time implementation	Sensitive to lighting and occlusion	∼99%
[3]	Multimodal (Vision + Sensors)	Improved recognition performance	High computational cost	∼98%
[4]	RGB Camera	Effective for ArSL recognition	Background sensitivity	∼99%
[5]	RGB Camera	High accuracy and scalability	Requires quality imaging conditions	∼98–99%
[6]	Radar	Privacy-preserving, works in darkness	Limited gesture resolution	∼96–98%
[7]	Micro-Doppler Radar	Robust activity recognition	Complex signal processing	N/A
[10]	Pose Estimation Camera	Robust to background clutter	Dependent on pose estimation quality	∼97%
[11]	Vision-Based Sensor	Simple deployment	Lower performance than modern DL models	∼95%
[12]	Video Camera + Transformer	Captures long temporal dependencies	Computationally expensive	∼98–99%
[13]	UWB Radar	Contactless and privacy-preserving	Specialized hardware required	∼97–99%
[14]	UWB Radar	Works without cameras and lighting	Limited public datasets	∼96–98%
[15]	Radar-Based Contactless Sensor	Privacy-preserving and robust	Hardware cost	∼98%
[17]	Video + IMU Sensors	Rich multimodal information	Requires wearable sensors	N/A
[18]	Vision-Based Sensor	Enables automatic sign decoding	Environmental sensitivity	∼98%
[19]	Electromagnetic Sensor	Works under varying visibility conditions	Limited adoption and datasets	N/A
[20]	RGB Video Camera	Supports continuous sign recognition research	Large annotation effort required	N/A

TABLE II

COMPARISON OF SIGN LANGUAGE DATASETS USED IN THE LITERATURE

Ref.	Language	Dataset Scale	# Signs	# Samples	# Participants	Public	Accuracy
[4]	Arabic SL	Medium	32–40	≈ 50,000 images	Multiple	No	∼99%
[13]	British SL	Limited	10–20	Thousands of radar frames	10–20	No	∼99%
[15]	British SL	Medium	24–40	Thousands of samples	Multiple	No	∼98%
[16]	ASL	Medium	26 letters	Several thousand images	Multiple users	Yes	N/A
[17]	Colombian SL (LSC50)	Medium	50	4000 videos	5	Yes	N/A
[20]	Qatari SL (JUMLA-QSL-22)	Large	22 words/sentences	>20,000 video segments	22 signers	Yes	N/A
[12]	Continuous SLR	Large	Continuous vocabulary	Large-scale video corpus	Multiple	No	∼99%

nition algorithms, which is essential for scientific validation and system comparison [8].

Nevertheless, many emerging sign language systems, especially those designed for regional languages, still rely on restricted datasets collected in controlled laboratory settings. This limitation restricts their practical use in real-world situations and obstructs the advancement of resilient recognition algorithms capable of generalizing across various contexts and user demographics [9].

To enhance recognition performance in underrepresented sign languages, it is essential to augment the dataset size, diversify the participant demographics, and standardize the acquisition protocols. See Table **??**.

C. Feature Extraction Techniques

Feature extraction is an essential element of sign-language recognition systems, as it dictates the representation and processing of gesture information by machine learning models. Older recognition systems used handcrafted features such as geometric descriptors and motion statistics. Newer systems, on the other hand, use deep feature representations extracted using convolutional neural networks [2].

Skeleton- and keypoint-based features derived from pose estimation algorithms facilitate efficient gesture tracking and real-time recognition performance [10].

Time-frequency representations, including spectrogram features, are extensively utilized for dynamic gesture recognition because they effectively capture temporal variations in motion signals [6].

Micro-Doppler features from radar sensors also provide detailed motion signatures that help with gesture classification in challenging environmental conditions [7]. See Table **??**.

D. Machine Learning Models

Machine learning models are crucial for systems that recognize sign language because they allow computers to automatically sort gestures and create time sequence models. Support vector machines and random forest algorithms are still useful for small datasets and structured feature representations [11].

However, deep learning models, especially convolutional neural networks (CNNs), are now the most common method for recognizing gestures in images because they can automatically detect hierarchical spatial features [1].

Long Short-Term Memory (LSTM) models and recurrent neural networks are frequently employed for dynamic gesture recognition owing to their capability to identify patterns in temporally varying data [3].

Recently, transformer-based architectures have demonstrated superior performance in continuous sign language recognition tasks by employing attention mechanisms to model long-range dependencies [12]. See Table IV.

TABLE III
FEATURE EXTRACTION TECHNIQUES USED IN SIGN LANGUAGE RECOGNITION

Ref.	Feature Extraction Technique	Input Modality	Strengths	Limitations
[1]	Multimodal Feature Fusion	Vision + Sensor Data	Combines complementary information and improves robustness	Increased computational complexity and synchronization requirements
[2]	Convolutional Feature Maps (CNN)	RGB Images/Videos	Automatically learns spatial hand features	Sensitive to lighting variations and occlusions
[3]	CNN + Temporal Feature Fusion	Multimodal Data	Captures both spatial and temporal information	Requires large training datasets
[4]	Deep CNN Features	RGB Images	Effective for hand shape and gesture representation	Performance depends on image quality
[5]	Hierarchical CNN Features	RGB Images/Videos	Extracts high-level gesture representations	Computationally intensive
[6]	Radar Micro-Doppler Features	Radar Signals	Privacy-preserving and robust to lighting conditions	Lower spatial resolution than cameras
[7]	Micro-Doppler Signatures	Radar Signals	Captures motion dynamics effectively	Complex signal preprocessing required
[10]	Human Skeletal Keypoints	Pose Estimation Data	Robust to background clutter and illumination changes	Dependent on pose estimation accuracy
[11]	Hand Geometry Features + ANN	Vision-Based Images	Simple and computationally efficient	Limited representation capability
[12]	Transformer Self-Attention Features	Video Sequences	Captures long-range temporal dependencies	Requires extensive computational resources
[13]	Residual Features (ResNet) + UWB Radar Features	UWB Radar	Deep hierarchical representation of radar signals	Specialized hardware required
[14]	Cumulative Distribution Density (CDD) Features	UWB Radar	Compact representation of gesture information	May lose fine-grained motion details
[15]	Deep Spatial Features (CNN)	Radar Data	Supports contactless recognition	Dataset-dependent performance
[16]	Image-Based Hand Features	ASL Images	Suitable for real-time applications	Limited temporal information
[17]	Multimodal Features (RGB, Depth, IR, IMU)	Video + IMU	Provides rich gesture representation	High storage and processing requirements
[18]	Deep Visual Features	RGB Images/Videos	Automatic feature learning	Sensitive to environmental variations
[19]	Attention-Augmented Electromagnetic Features	Electromagnetic Signals	Enhances important gesture characteristics	Limited availability of datasets
[20]	Spatiotemporal Video Features	Continuous Video Sequences	Suitable for continuous sign language recognition	Requires extensive annotation effort

III. CURRENT STATUS OF TUNISIAN SIGN LANGUAGE RECOGNITION (A DIAGNOSTIC SECTION)

In recent years, research on recognizing Tunisian Sign Language has made great strides, especially with the use of machine learning and deep learning methods for gesture classification. Researchers have investigated the use of convolutional neural networks and image-based recognition frameworks to identify both static and moving gestures. These efforts are important steps toward developing automated communication tools for deaf people in Tunisia.

However, the technology we currently have shows that there are some structural problems that limit system performance and long-term growth.

First, there are not many datasets available. Most datasets for Tunisian Sign Language are small and come from a small number of people in controlled indoor settings. The lack of variety makes it difficult for machine learning models to work with different users, backgrounds, and environmental conditions. In real-world situations, these limitations often lead to lower accuracy in recognition and unpredictable behavior of the system.

Second, most sensing modalities used in current systems are based on vision. Cameras are easy to find and have high spatial resolution, but they do not work well in low light, with a lot of background noise, or when something is blocking the view. These limitations are especially clear in real-world situations, such as when people are outside or talking at night. Therefore, systems that only use visual sensing may have trouble maintaining their performance outside of the laboratory.

Third, the real-time implementation of Tunisian Sign Language research is still not well understood. Many recognition systems are tested offline with recorded datasets, and little consideration is given to latency, computational efficiency, or embedded deployment. For assistive communication technologies, real-time performance is not only a technical feature but also a basic requirement for usability.

Finally, the lack of standardized evaluation protocols is a significant problem. It is difficult to compare results from different studies or see how the research community is performing without consistent benchmarks. To advance the field, it is important to establish procedures for acquiring data and performance metrics that can be repeated.

These observations indicate that research on Tunisian sign language recognition is evolving from an exploratory phase to a more advanced stage of system development. To develop recognition systems that work well and can be used by many people, it is important to address the problems that have been

TABLE IV
COMPARISON OF DEEP LEARNING MODELS FOR SIGN LANGUAGE RECOGNITION

Ref.	Model	Dataset / Language	Approach	Accuracy
[1]	CNN, LSTM, Transformer (Review)	Multiple datasets	Multimodal sensor-based SLR review	N/A
[2]	CNN	Sign language image dataset	Real-time sign language recognition	∼99%
[3]	CNN-LSTM	Multimodal SLR dataset	Multimodal deep learning framework	∼98%
[4]	CNN	Arabic Sign Language	Deep learning framework for ArSL recognition	∼99%
[5]	Deep CNN	Sign language image dataset	Deep learning-based SLR system	∼98–99%
[6]	CNN + Radar Processing	Radar gesture dataset	Radar-based gesture recognition	∼96–98%
[10]	Pose Estimation + LSTM/CNN	Skeleton-based SLR dataset	Pose-based sign language recognition	∼97%
[11]	Artificial Neural Network (ANN)	Sign gesture dataset	ANN-based gesture classification	∼95%
[12]	Transformer	Continuous SLR dataset	Continuous sign language recognition	∼98–99%
[13]	ResNet + UWB Radar	British Sign Language	UWB radar sensing with residual neural network	∼97–99%
[14]	Deep Neural Network + UWB Features	Gesture/Sign dataset	UWB radar-based gesture recognition	∼96–98%
[15]	CNN	British Sign Language	Contactless and privacy-preserving recognition	∼98%
[16]	Dataset Paper	ASL Dataset	Real-time recognition dataset for LLM integration	N/A
[17]	Dataset Paper	Colombian Sign Language (LSC50)	Video and IMU dataset for SLR research	N/A

identified.

IV. Areas of Improvement and Future Directions for Tunisian Sign Language Recognition (TSLR)

Based on the analysis of existing Tunisian Sign Language Recognition (TSLR) systems and the evolution of global sign language technologies, several critical areas for improvement can be identified. These areas reflect the technological, methodological, and operational limitations that currently constrain system robustness, scalability, and real-world deployment.

A. Direction 1: Development of Large-Scale Multimodal Datasets

One of the primary limitations of current TSLR research is the restricted size and diversity of the available datasets. Large datasets with gestures from different people recorded in different settings make it much easier for models to generalize and recognize the gestures. These datasets also help create standardized benchmarks, which allow researchers to compare algorithms and observe how things change over time.

Future research should prioritize the creation of comprehensive datasets that capture real-world communication scenarios.

Key objectives include:

- Include a larger number of participants with different ages, genders, and signing styles [16], [18], [20];
- Capture gestures in diverse environmental conditions (indoor, outdoor, low-light [12]);
- Support continuous sign sequences rather than isolated gestures;
- Provide standardized annotations and metadata;
- Collection of multimodal gesture data (RGB, depth, radar, IMU);
- Inclusion of diverse signer populations;
- Recording in real-world environments;
- Continuous sign language sequence annotation.

This area directly affects the robustness, reproducibility, and reliability of the model.

B. Area 2: Sensing Modality Enhancement

Existing Tunisian Sign Language recognition systems predominantly rely on RGB cameras. Although effective in controlled settings, camera-based systems are sensitive to lighting conditions, occlusions, and background complexity. Increasingly, modern sign language recognition systems use more than one sensor, such as RGB cameras, depth sensors, inertial measurement units, and radar devices. Each sensing modality provides the system with more information, allowing it to continue functioning even if one sensor is affected by environmental limits. For instance, depth sensors make motion tracking more accurate, and radar sensors can detect gestures in low-light or visually obstructed areas.

Advancing Tunisian Sign Language Recognition requires a coordinated effort across sensing technologies, artificial intelligence methods, system deployment, and community engagement. The following future directions outline a structured roadmap for technological and research developments.

The opportunities for improvement include the following:

- Integration of multimodal sensing technologies;
- Use of depth sensors for spatial motion tracking;
- Adoption of inertial sensors for motion dynamics;
- Exploration of radar sensing for non-visual gesture detection [14], [15], [19].

Multimodal sensing improves system reliability and environmental adaptability.

C. Area 3: Feature Representation and Motion Modeling

Current feature extraction methods often focus on static hand shapes and frame-based visual features. However, sign language is inherently dynamic and requires temporal modeling.

The key improvement directions include the following:

- Skeleton-based hand and body tracking;
- Temporal motion trajectory modeling;
- Spatiotemporal feature extraction;
- Multi-joint motion representation.

Improved feature representation enables the accurate recognition of dynamic gestures and complex sign sequences.

D. Area 4: Machine Learning Model Optimization

Many existing systems use standard convolutional neural networks (CNNs) without fully leveraging advanced sequence modeling techniques.

Potential improvements include the following:

- Transformer-based architectures for sequence learning;
- Hybrid CNN-LSTM models for temporal recognition;
- Lightweight neural networks for embedded deployment;
- Transfer learning and domain adaptation strategies.

Model optimization directly influences the recognition accuracy, latency, and computational efficiency.

E. Area 5: Employment of Real-Time Embedded Recognition Systems

Future systems should be designed for practical, real-world operations on portable and embedded platforms.

The key research areas include:

- Edge computing implementation;
- Mobile device integration;
- Low-power neural network architectures;
- Real-time inference optimization;
- Real-time gesture detection pipelines;
- Low-latency inference mechanisms;
- Edge computing implementation;
- Hardware acceleration (GPU or embedded processors);
- Mobile device integration;
- Low-power neural network architectures;
- Real-time inference optimization.

Embedded deployment enables the use of accessible assistive communication technologies.

Most TSLR systems are evaluated offline using pre-recorded datasets. Real-time communication requires low latency and consistent performance.

Sensor fusion enhances the stability of the system across various environmental conditions.

Real-time capability is essential for practical, assistive communication systems.

F. Area 6: Environmental Robustness and System Reliability

Recognition accuracy often decreases under challenging environmental conditions, such as low lighting, motion blur, or occlusion.

The improvement strategies include the following:

- Robust gesture detection under variable lighting;
- Noise-resistant feature extraction;
- Multi-sensor fusion techniques;
- Adaptive model calibration.

Environmental robustness is a key requirement for deployment in real-world settings.

G. Area 7: Standardization and Benchmarking

The absence of standardized evaluation protocols limits the comparability of the research results.

The necessary improvements include the following:

- Standard dataset acquisition protocols;
- Unified performance metrics;
- Reproducible evaluation procedures;
- Public dataset repositories.

Standardization supports scientific reproducibility and long-term research.

H. Area: Human-Centered System Design

Effective recognition systems must align with the needs of the deaf communities.

Future research should emphasize the following:

- User-centered interface design;
- Accessibility testing;
- Real-world usability evaluation;
- Community collaboration.

Human-centered design [17] ensures that technological innovations are translated into practical communication solutions.

Studies on prevalent sign languages yield significant insights into the technological elements that facilitate the development of resilient and scalable recognition systems. By examining these systems, useful strategies that can be used in Tunisia can be identified.

I. Area: Integration of Radar-Based Gesture Recognition

Radar-sensing technologies [6], [15], [19] offer unique advantages for gesture recognition, particularly in conditions in which vision-based systems perform poorly.

Future research should explore the following:

- Micro-Doppler-based hand motion detection [7];
- Radar-based gesture classification models;
- Privacy-preserving sensing systems;
- Low-light and nighttime gesture recognition.

Radar technology is a promising complementary sensing modality for next-generation TSLR systems.

J. Area: Implementation of Multimodal Sensor Fusion

The combination of multiple sensors can significantly improve recognition reliability and robustness [1].

The research priorities are as follows:

- Fusion of camera, depth, and radar signals;
- Multimodal feature integration frameworks;
- Sensor synchronization algorithms;
- Robust decision-level fusion methods.

Sensor fusion enhances the stability of the system across various environmental conditions.

Embedded deployment enables the use of accessible assistive communication technologies.

K. Area: Continuous Sign Language Recognition

Most current systems focus on the recognition of isolated gestures. However, natural communication involves continuous signing in a dynamic environment.

Future studies should address the following issues.

- Continuous gesture segmentation;
- Temporal sequence modeling;
- Context-aware recognition;
- Sentence-level translation systems.

Continuous recognition is the next major milestone in sign language technology.

V. Conclusion

This study provided a diagnosis of Tunisian Sign Language recognition systems and those created for other sign languages. The analysis identified significant technical deficiencies in dataset accessibility, sensing modalities, and system implementation, which hinder the effectiveness of Tunisian sign language recognition systems compared to those for other sign languages.

Lessons learned from established sign language recognition systems can provide valuable guidance for developing and enhancing Tunisian sign language recognition frameworks. Studies conducted on widely used sign languages have demonstrated that system robustness and scalability are strongly influenced by dataset quality, sensing modalities, and real-time implementation capabilities.

The following improvements are recommended based on the best practices observed in global sign language research:

- Develop standardized datasets to ensure reproducibility and enable consistent benchmarking across studies;
- Increase participant diversity to improve model generalization across different users and signing styles;
- Implement multimodal sensing approaches to enhance recognition reliability under varying environmental conditions;
- Integrate radar sensing technology to support gesture detection in low-light, occluded, or privacy-sensitive environments;
- Validate real-time system performance to ensure practical usability in assistive communication scenarios.

These actions can significantly improve the reliability, robustness, and scalability of Tunisian Sign Language recognition systems, facilitating their transition from controlled laboratory prototypes to real-world assistive technologies.

Therefore, adding radar technology to systems that recognize Tunisian Sign Language is a promising area of research. Future systems can be more reliable, scalable, and useful in real life for deaf and mute communities if they use what we already know about sign language and modern sensing technologies.

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