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A REVIEW OF SIGN LANGUAGE EVOLUTION AND TECHNOLOGICAL ADVANCEMENTS: SPOTLIGHT ON QURANIC SIGN LANGUAGE DEVELOPMENT

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Abstract— This paper presents a comprehensive review of the evolution of sign languages, with a particular emphasis on Arabic Sign Language (ArSL) and the emerging field of Quranic Sign Language (QSL). It outlines the shift from early manual-coded systems to natural sign languages and highlights technological advancements in Sign Language Recognition (SLR) and Sign Language Production (SLP) driven by deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and

LSTM, Quranic Sign Language, Sign Language Recognition	Transformers. The review critically examines existing ArSL datasets, model performances, and production systems, drawing attention to the disparity in resources between Western and Arabic sign languages. It also explores the development of QSL systems designed to support Deaf Muslims in learning Quranic content, focusing on CNN-based gesture recognition models for Hijāʾīyah letters. Despite notable progress, QSL systems remain limited to isolated gesture recognition due to dataset scarcity and theological complexity. The paper concludes by identifying key challenges in temporal modeling, signer independence, and religious accuracy, and proposes future directions to enable inclusive, AI-driven Quranic education for the Deaf community.

I. Introduction

Sign languages are complex visual-spatial languages with their own grammar, morphology, and expressions that extend far beyond direct word-to-word translation. They rely on spatial structuring, facial expressions, and non-manual markers to convey meaning, enabling multiple layers of information to be communicated simultaneously [1]. Natural sign languages such as American Sign Language (ASL), British Sign Language (BSL), and Arabic Sign Language (ArSL) have evolved organically within Deaf communities. ArSL exhibits diverse dialects across Arab nations and does not follow the syntax of spoken Arabic, making it a distinct linguistic system [2].

Technological exploration in Sign Language Recognition (SLR) began in the 1970s, initially involving robotic hands like RALPH and later progressing to sensor-based gloves for capturing hand motion and finger articulation [3]. While these early systems marked an important step, they were constrained by their mechanical design, signer dependency, and the lack of scalable linguistic modelling. A transformative shift occurred with the adoption of computer vision, particularly using Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models [4-5]. These methods enabled the automatic extraction of spatial-temporal features from video data, allowing real-time and signer-independent recognition of sign gestures with high accuracy on datasets such as ArSL2018 and ArabSign [6].

In parallel, Sign Language Production (SLP) the generation of sign language output from spoken or written language emerged with avatar-based translation systems. Technologies such as X3D and H-Anim standards have enabled the development of animated 3D signers for educational environments, religious applications, and public service announcements [7]. These avatars are particularly useful where human interpreters are not available or where automation is essential for scale and accessibility.

A recent and significant innovation in this domain is the emergence of Quranic Sign Language (QSL) systems, which aim to provide Deaf Muslims with access to Quranic recitation and understanding. QSL differs from general ArSL in that it requires precise theological fidelity and specialized gestures to convey sacred texts and Tajwīd rules. Malaysia's OTTS (Online Quranic Tadarus Without Voice) application is one such example, enabling users to practice Quranic letters in sign form and receive feedback on their recitation attempts [8].

CNN-based models have been applied to QSL-related datasets, particularly the ArSL2018 subset focused on the 14 Hijā'īyah letters used in Quranic verses. These systems have achieved classification accuracies above 97% using SMOTE-based augmentation and letter-specific CNN classifiers [9-10]. Despite this progress, QSL remains limited to static letter recognition and lacks the continuous verse-level modelling found in general ArSL systems a gap this review aims to address by synthesizing current methods and outlining areas for future expansion.

II. Methodological Approach

This review adopts a systematic and thematic synthesis of literature related to SLR and QSL development. The selection was guided by the following criteria:

- Databases used: IEEE Xplore, Scopus, SpringerLink, MDPI, ScienceDirect.
- Search keywords: “Quranic Sign Language Recognition,” “Arabic Sign Language CNN,” “Deep Learning in SLR,” “QSL datasets,” “LSTM sign recognition”.
- Year range: 2015 to 2025, focusing on deep learning evolution relevant to Quranic/Arabic sign systems.

The aim was to compare both mainstream ArSL systems and QSL-specific adaptations, while identifying challenges in scalability, signer-dependence, and religious accuracy. A comparative synthesis table (see Section VI) was also constructed to highlight the differences between general ArSL and QSL systems including dataset characteristics, model architecture, recognition accuracy, and application purpose.

III. Evolution of Sign Language

A. Manual vs. Natural Sign Systems

The development of sign languages can be broadly divided into two major categories which are manual coded systems and natural sign languages. Manual coding systems, such as Kod Tangan Bahasa Malaysia (KTBM), were developed with the primary aim of assisting Deaf students in acquiring the national spoken language, in this case, Bahasa Malaysia [11]. KTBM is not a fully-fledged language but rather a signed version of spoken Malay that mirrors its syntax and grammar, making it highly structured but unnatural in use. Similar systems exist globally, including Signing Exact English (SEE) and Manually Coded Arabic. These systems are primarily used in educational contexts but lack the rich linguistic features of natural sign languages.

In contrast, natural sign languages evolve organically within Deaf communities. They possess fully developed grammars, including spatial indexing, classifier systems, and non-manual grammatical markers such as eyebrow movement, body tilt, and head position [12]. One such family is the Arab Sign-Language family, which includes Egyptian Sign Language, Jordanian Sign Language, and other regionally distinct systems. Despite regional variation, there has been an effort to unify these dialects into a standardised form known as Unified Arabic Sign Language, promoted by organisations such as the Council of Arab Ministers of Social Affairs (CAMSA) [1]. However, these unification attempts have often been met with community resistance due to grammatical inconsistency, cultural specificity, and signer familiarity with local dialects [13-14].

In the context of Quranic education, natural sign languages are far better suited than coded systems like KTBM because they allow for the nuanced expression of theological concepts, emotional tone, and verse structure all critical elements in accurate Quranic recitation and interpretation. Therefore, most modern research in sign language recognition, including QSL, focuses on leveraging the structures of natural sign languages rather than artificial codified systems.

B. Dataset and Recognition Milestones

Despite the increasing global interest in sign language recognition, Arabic Sign Language (ArSL) remains significantly under-resourced compared to widely studied sign

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languages such as ASL or BSL. This scarcity is particularly evident in the availability of large-scale, well-annotated datasets for training and benchmarking machine learning models [5]. While ASL enjoys several continuous signing corpora with tens of thousands of samples, many ArSL datasets are limited to isolated words, alphabet letters, or simple phrases, often lacking signer diversity or depth data.

A notable development in this regard is the ArabSign dataset, a publicly released multi-modal corpus designed to advance continuous ArSL recognition. It contains over 9,335 signed sentences annotated with RGB, depth, and skeleton information, allowing for rich spatial-temporal modelling [5]. ArabSign serves as a critical benchmark for developing models capable of handling continuous gesture transitions and sentence level understanding in Arabic sign contexts. This is essential groundwork for scaling QSL systems beyond letter-level recognition.

In terms of performance, hybrid architectures such as CNN-LSTM have shown promising results. Studies using Saudi-based ArSL datasets reported accuracy levels ranging from 82% to 94% for isolated gestures, depending on whether the input was static (single frame) or dynamic (temporal sequences) [15]. CNNs were typically responsible for spatial feature extraction, while LSTMs captured the temporal flow of gestures a setup that has now become a baseline in many ArSL recognition pipelines.

However, it is important to note that these milestones are largely constrained to general communication contexts. The QSL remains outside the scope of these large-scale datasets. Most QSL systems still rely on limited, handcrafted datasets that only represent a subset of Hijā’īyah letters used in Quranic recitation. These datasets are often not publicly available, making replication and further development difficult for researchers.

The disparity in dataset quality and size between general ArSL and QSL systems presents one of the most significant bottlenecks in current research. Bridging this gap will require not only data collection initiatives across Islamic institutions and Deaf communities but also careful attention to theological accuracy and signer inclusivity during annotation.

IV. Technological Advances in ArSLR and SLP

Technological advancements in Arabic Sign Language Recognition (ArSLR) and Sign Language Production (SLP) have undergone a significant transformation over the past decade, primarily due to the rise of deep learning, sensor integration, and the availability of improved datasets. These innovations have not only improved the accuracy of sign recognition systems but have also laid the foundation for niche applications such as QSL [6][9].

A. Architectures for ArSLR

Early ArSLR systems relied on traditional machine learning techniques such as Hidden Markov Models (HMMs), Support Vector Machines (SVMs), and k-Nearest Neighbors (k-NN), often requiring handcrafted features such as geometric trajectories, motion vectors, and gradient histograms [14][16]. While these approaches provided limited recognition for isolated signs, they lacked the robustness to generalise across signers or handle continuous sequences.

The transition to CNNs marked a significant leap in SLR. CNNs automatically learn spatial features from image sequences, making them especially effective for recognizing isolated static gestures, such as hand-postured alphabets [17]. Balat et al. demonstrated that fine-tuned CNNs applied to the ArSL2018 and AASL datasets can exceed 99% recognition accuracy [4]. To further improve efficiency, lightweight transfer learning models such as MobileNetV3, EfficientNet-B2, and Swin Transformers have been adopted to retain high accuracy while minimising computational cost [18].

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For continuous gesture recognition, CNNs are combined with RNNs, particularly Long Short-Term Memory (LSTM) or Bidirectional LSTM (BiLSTM) networks, which capture temporal dependencies in sequential data [5]. This hybrid CNN-BiLSTM architecture forms the basis for many high performing models in continuous ArSL recognition. A recent study integrating Temporal Convolutional Networks (TCNs) with BiLSTM outperformed baseline RNNs, achieving 99.5% accuracy on sentence-level ArSL tasks while reducing training time [19].

Despite these advances, Arabic SLR still faces a dataset bottleneck. While ASL benefits from large, publicly available corpora, ArSL research often relies on smaller, isolated-word datasets with limited signer diversity. The introduction of ArabSign, a multimodal dataset with RGB, depth, and skeleton data covering over 9,000 sentences, has started to address this gap, providing a benchmark for continuous sentence-level modelling [20-21].

V. Quranic Sign Language Development

A. Educational Motivation

The QSL is a domain-specific application of SLR technology designed to promote equitable access to Quranic education for Deaf Muslims. Unlike general ArSL, which focuses on conversational or lexical communication, QSL encodes religious concepts such as Tajwīd, Hijā’īyah phonetics, and verse semantics [22]. This necessitates high precision in gesture recognition and production to preserve theological accuracy.

Traditional Islamic learning methods, such as talaqqī musyāfahah (face-to-face Quranic transmission), rely on oral repetition and instructor feedback. This pedagogical model inherently excludes learners who are Deaf or hard of hearing. Therefore, QSL development is not only a technological innovation but also a spiritual inclusion initiative [8].

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Institutions such as USIM's Ummi Maktum Centre in Malaysia have pioneered efforts to formalise QSL through structured training, development of QSL dictionaries, and digital learning platforms [23]. Similarly, Indonesian researchers have developed the Kitabah and Tilawah methods to teach Quranic content using adapted sign representations [24].

B. System Motivation

Most current QSL systems focus on letter-level recognition, particularly the 14 dashed Hijā'īyah letters (e.g., ث, ت, ب), which are critical for correct Quranic pronunciation. CNN-based models have demonstrated high accuracy in this domain. AbdElghfar et al. developed a CNN trained on 24,137 images of these letters, achieving accuracy rates above 97% [9].

Attempts to build continuous QSL recognition systems are ongoing, but progress is constrained by the absence of annotated, standardised datasets. The theological sensitivity of Quranic content also limits data-sharing and large-scale annotation efforts, making it difficult to crowdsource gesture videos or validate generalisation across different regions [20].

C. Integration with Deep Learning Architectures

To move beyond isolated letter recognition, QSL systems must incorporate temporal modelling architectures, such as BiLSTM, TCN, and Transformers. These models can capture the rhythm, order, and prosody of recited Quranic phrases, enabling verse-level recognition [5][19].

Few experimental efforts have explored this space. Some prototype systems attempt to segment a recited ayah into hand gestures and map them through LSTM-based decoders, but these remain unpublished or exist only in closed institutional trials [25]. Future QSL systems should consider:

- Signer Independence: Generalise models across users with different hand shapes, speeds, and signing styles.

- Time-sensitive Modelling: Preserve Quranic rhythm and verse pauses.
- Semantic Validity: Ensure that generated signs or interpretations are theologically sound and contextually accurate.

Despite its limitations, QSL is emerging as a powerful tool for faith-based empowerment, supporting the global movement toward inclusive Islamic education through AI.

VI. Comparative Analysis

A. Dataset Size and Type

General ArSL benefits from larger and multi-modal corpora such as ArabSign, which includes color, depth, and skeleton annotations with over 9,000 sentence samples [5] QSL, by contrast, relies on a smaller set of letter-level images focused on Quranic dashed letters (~24,000 samples) which limits continuous or sentence level recognition [9].

B. Recognition Accuracy

General ArSL systems leveraging Transformers or TCN models have achieved recognition rates up to ~99.6 % on isolated and continuous sign tasks [4][18]. The QSL system with a CNN trained on letter images plus data augmentation achieved slightly lower accuracy of ~97–98 % when classifying 14 distinct Quranic letters [9].

C. Application Purpose

General ArSL technology aims to support broad communication, translation, and accessibility across domains. QSL is purpose built for supporting Quran recitation and memorization for Deaf learners, addressing a specific educational and religious gap.

D. Model Complexity

The latest general models use complex architectures transformer based ViT, Swin, Hybrid CNN LSTM, TCN, and attention-guided U Net variants [4][18]. QSL models are currently simpler primarily CNNs without temporal modelling optimized for static letter signs and requiring less computational resources [9].

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E. Standardization Status

While projects like ArabSign begin to offer a unified resource and some community-driven sign standardization exists for ArSL [5], QSL remains localized existing methods in Indonesia and Malaysia remain non standardized and limited to letter recognition rather than full verse level grammar.

Table 1 compares the ArSL and QSL recognition studies.

Table 1: Comparitive Table of ArSL and QSL Recognition

Domain	General ArSL Recognition	Quranic Sign Language (QSL) Letter Recognition
Dataset Size and Type	Large datasets like ArSL2018, ArabSign (sentence-level and multi-modal) [5]	Smaller curated subset: 14 dotted Quranic letters, ~24,137 images [9]
Recognition Accuracy	State of art models achieve ~99.5-99.6 % (Transformers, TCN) [4][18]	CNN based QSL model achieves ~97-98 % accuracy on letter classification [9]
Application Purpose	General communication, translation, accessibility.	Religious education: Qur'an letter recitation and memorization.
Model Complexity	Transformers, hybrid CNN-LSTM, TCN, G-Tversky architectures [16]	CNN only architectures with data augmentation and SMOTE [9]
Standardization Status	ArabSign emerging; limited standard grammar [5]	At early stage, country specific QSL methods, not yet standardized.

VII.Conclusion

This review has explored the evolution of sign language systems, focusing on ArSLR, and the emerging field of QSL. From early manual-coded systems like KTBM to natural sign languages rich in grammar and spatial morphology, the linguistic foundation for sign language technologies has matured significantly. Technological advancements particularly in deep learning have enabled high-accuracy recognition of Arabic sign gestures, with hybrid models such as CNN-BiLSTM and transformer-based architectures demonstrating strong performance on isolated and continuous ArSL datasets.

However, QSL systems remain in a developmental stage, primarily limited to static letter recognition due to constrained datasets and the lack of standardised theological frameworks. Despite this, initiatives in Malaysia, Indonesia, and the broader Muslim world reflect a growing awareness of the importance of inclusive religious education. These early efforts point to the promising role of artificial intelligence in supporting spiritual empowerment for Deaf Muslims.

VIII. Acknowledgement

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