KARYA ILHAM PUBLISHING
CONNECTING MINDS, BRIDGING IDEAS, INSPIRING READERS

Journal of Advanced Research in Social and Behavioural Sciences

Journal homepage:
https://karyailham.com.my/index.php/jarsbs/index
ISSN: 2462-1951



Digitalising Quranic Learning through Artificial Intelligence: LSTM-Based Verse Identification from Audio Recitations

Muhammad Amirul Shamsul Kamal[1], Noor Hasimah Ibrahim Teo[1,*]

[1] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Melaka, Malaysia

ARTICLE INFO

Article history:
Received 1 October 2026
Received in revised form 6 November 2026
Accepted 10 November 2026
Available online 20 November 2026

Keywords:
Artificial intelligence; Quranic learning; Quranic recitation; LSTM; MFCC; verse identification; Tasmik; Muraja'ah

ABSTRACT

Artificial intelligence (AI) offers new opportunities to extend Quranic learning beyond static digital resources toward interactive recitation support. However, learners practising independently still have limited access to immediate verse-level recognition, while formal recitation assessment remains dependent on qualified teachers. This study develops and evaluates an AI-assisted Quranic verse-identification approach using Mel-Frequency Cepstral Coefficients (MFCC) and Long Short-Term Memory (LSTM), and demonstrates its integration into a mobile application as supplementary support for Muraja'ah and preliminary Tasmik. Audio recitations from Surah Al-Ikhlas, An-Nas, and Al-Fatihah were standardised, augmented, converted into 13-coefficient MFCC sequences, and classified using separate LSTM models. Performance was assessed using accuracy, precision, recall, F1-score, loss, and confusion matrices. Test accuracies were 90.21% for Al-Ikhlas, 70.75% for An-Nas, and 74.83% for Al-Fatihah, with most errors concentrated among specific acoustically similar verse pairs. The trained models were integrated into a mobile application that records a recitation and highlights the predicted verse. The findings demonstrate the feasibility of constrained MFCC-LSTM verse identification for independent revision, while confirming that the system should complement rather than replace teacher-led Quranic instruction. The current model does not assess Tajwid, makhraj, or pronunciation quality.

1. Introduction

Artificial intelligence (AI) and mobile technologies are increasingly extending Quranic learning from digital text and prerecorded audio toward interactive systems that can respond to a learner's own recitation. Recent work suggests that AI can support independent memorisation and revision, but should remain complementary to the teacher-student relationship that underpins Quranic learning [1]. This distinction is especially important in Tahfiz education, where digital convenience must not be interpreted as a replacement for authoritative recitation guidance.

Quranic memorisation depends on repeated retrieval, verification, and correction. Two established practices are Tasmik, in which memorised passages are recited for listening and verification, and Muraja'ah, which involves systematic repetition of previously memorised passages to maintain retention and fluency. Studies of Tahfiz practice consistently describe the two methods as complementary: Muraja'ah sustains memorisation while Tasmik provides external checking and

* *Corresponding author.*
E-mail address: shimateo@uitm.edu.my

correction [2-6]. During independent study, however, learners may not have immediate access to a teacher or listener, creating a practical need for supplementary tools that support revision between formal sessions.

Digital Quran applications increasingly address this need through repetition, progress monitoring, voice interaction, and AI-assisted feedback. Reviews of Quran memorisation technologies show a transition from conventional reading applications toward more interactive learning support [7]. Recent studies of AI-enabled applications report potential benefits for memorisation and Muraja'ah, including voice recognition, adaptive support, and immediate feedback, while also highlighting concerns about recognition accuracy, religious sensitivity, privacy, and over-reliance on automation [8-16]. These findings support a hybrid model in which technology expands practice opportunities while teachers remain responsible for qualitative recitation assessment.

Automatic processing of Quranic recitation is technically challenging because recognition is affected by speaker identity, pronunciation, tempo, pitch, recording conditions, and acoustic similarity between verses. Arabic automatic speech recognition also continues to face limitations in data availability and linguistic variability [17]. Quranic speech research has therefore progressed from conventional feature engineering toward deep and end-to-end models for reciter identification, transcription, phoneme recognition, and recitation analysis [18-24]. Dataset studies further show that speaker diversity is important: systems trained mainly on proficient adult male reciters may generalise poorly to learners of different ages, genders, accents, and proficiency levels [19,20].

For constrained audio classification, Mel-Frequency Cepstral Coefficients (MFCC) remain a useful representation of short-term speech spectra. Their use in speech recognition originates from early work demonstrating the discriminative value of mel-frequency cepstral representations [25]. In Quranic audio, MFCC features have produced strong results for reciter identification and related classification tasks [26,27]. Long Short-Term Memory (LSTM) networks are designed to learn dependencies across sequential observations [28], making them appropriate for time-ordered MFCC sequences. Nigar *et al*., [29] demonstrated the compatibility of MFCC and LSTM-RNN within an intelligent Quran-learning framework, although their task differed from the verse-level classification addressed here.

The present study focuses on verse identification rather than unrestricted speech transcription or automated judgement of recitation correctness. The system receives a recited passage, extracts MFCC features, predicts the corresponding verse with an LSTM classifier, and highlights that verse in a mobile application. This narrower task is intended to provide immediate verse-level confirmation during independent Muraja'ah and a preliminary self-check before teacher-led Tasmik. It does not evaluate Tajwid, makhraj, or pronunciation quality, and therefore does not replace formal Tasmik or Tahsin instruction.

1.1 Synthesis of Related Studies and Research Gap

Table 1 summarises representative studies at the intersection of Quranic pedagogy and Quranic speech technology. Existing pedagogical studies establish the importance of repetition and verification but generally do not implement automatic acoustic recognition, whereas technical studies commonly target reciter identity, transcription, phoneme recognition, or pronunciation analysis rather than verse identification as a learning interaction [2,7,8,19-24,26,27,29].

Table 1
Comparison of representative studies related to AI-assisted Quranic learning

Study	Main focus	Approach/technology	Main relevance	Gap relative to present study
Luthfiah and Syarif [2]	Tasmik and Muraja'ah	Quranic pedagogy	Establishes recitation verification and systematic revision practices	No AI/audio-recognition component
Haryono *et al*., [7]	Quran memorisation technologies	Review of 31 studies and 12 apps	Demonstrates growth of technology-supported memorisation	No specific verse-recognition model
Mustapa *et al*., (2025)	AI for Quran memorisation	Tarteel/AI speech recognition review	Links AI with memorisation and revision	Evaluates existing application rather than developing an acoustic model
Osman *et al*., [19]	Quranic audio dataset	QDAT, >1,500 annotated samples	Provides Quranic speech data for ML/DL	Focused on recitation-rule correctness
Al-Issa *et al*., [20]	Quranic ASR inclusiveness	QRFAM/DeepSpeech	Highlights gender and speaker-generalisation problem	Full speech recognition rather than verse classification
Samara *et al*., [26]	Quran reciter recognition	MFCC + CNN	Demonstrates effectiveness of MFCC for Quranic audio	Classifies reciter identity, not verse
Nigar *et al*., [29]	Intelligent Quran learning	MFCC + LSTM-RNN	Closest technical combination to current work	Broader pronunciation/Tajwid learning objective
Hadwan *et al*., [21]	Quranic ASR	Transformer encoder-decoder	Strong end-to-end Quran transcription	Higher-complexity transcription task
Al-Zaro *et al*., [23]	Speaker-independent Quran ASR	Deep learning/phoneme modelling	Addresses diverse user populations	Phoneme-level ASR rather than verse identification
Present study	AI-assisted Quranic verse identification for digital learning	MFCC + LSTM + mobile application	Links verse recognition to Tasmik and Muraja'ah	Restricted to three selected Surahs

The comparison identifies a gap between established Quranic learning practices and lightweight verse-level speech classification. The present study addresses this gap by implementing an MFCC-LSTM classifier and operationalising its output in a mobile learning application. Its contribution is therefore both technical, through verse-level recognition across three selected Surahs, and pedagogical, through a deliberately supplementary role for Muraja'ah and preliminary Tasmik.

Accordingly, the study has three objectives: (1) to develop an MFCC-LSTM approach for identifying Quranic verses from audio recitations; (2) to evaluate recognition performance for Surah Al-Ikhlas, An-Nas, and Al-Fatihah; and (3) to demonstrate integration of verse identification into a mobile application as supplementary support for Muraja'ah and preliminary Tasmik. The scope is limited to multiclass verse identification for these three Surahs; it does not cover unrestricted Quranic transcription or automatic Tajwid, makhraj, or pronunciation assessment.

The proposed relationship between Quranic pedagogy, audio processing, verse identification, and learner support is shown in Fig. 1.

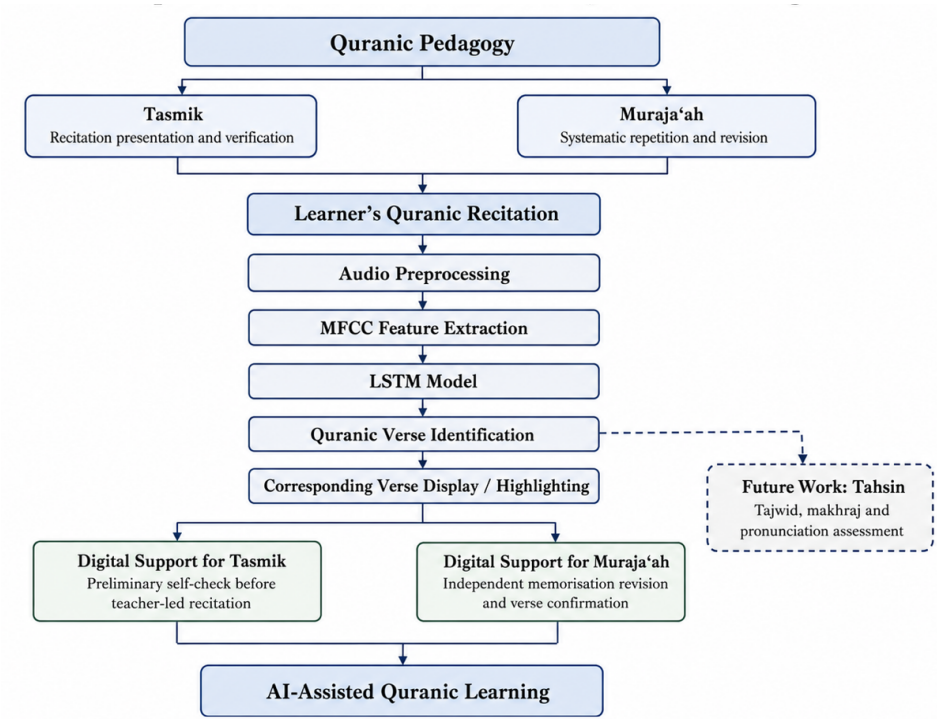

Fig. 1. Conceptual framework

2. Methodology

An experimental deep-learning approach was used to develop separate verse classifiers for Surah Al-Ikhlas, An-Nas, and Al-Fatihah and to integrate the trained models into a mobile Quranic learning application. The workflow comprised audio acquisition, augmentation and standardisation, MFCC extraction, verse labelling, normalisation, LSTM training, held-out evaluation, and application integration.

2.1 Dataset and Audio Preprocessing

Quranic recitation recordings were collected from publicly accessible Quranic audio repositories and online sources identified in the project report. Samples were selected to include variation in voice, accent, rhythm, speed, and tonal characteristics. All recordings were converted to WAV at 16 kHz. Data augmentation introduced Gaussian noise, time stretching, pitch shifting, and gain adjustment while retaining the original verse label. Following augmentation, the datasets contained 6,024 samples for Al-Ikhlas, 2,571 for An-Nas, and 2,241 for Al-Fatihah. The within-Surah class distributions were relatively balanced, as shown in Table 2.

Table 2
Distribution of Quranic audio samples

Surah	Verse	Number of Samples
Al-Ikhlas	1	1,500
	2	1,512
	3	1,504
	4	1,512
Total Al-Ikhlas		6,024
An-Nas	1	427
	2	429
	3	426
	4	422
	5	423
	6	444
Total An-Nas		2,571
Al-Fatihah	1	333
	2	320
	3	322
	4	318
	5	320
	6	310
	7	318
Total Al-Fatihah		2,241

Each recording was transformed into 13 MFCC coefficients. Because recording durations differed, MFCC matrices were standardised to 50 time steps by padding shorter sequences and truncating longer ones, producing a fixed 50 x 13 input representation. Verse labels were derived from the verse identifiers embedded in filenames, mapped to zero-based class indices, and one-hot encoded. MFCC values were then z-score normalised before training.

2.2 MFCC-LSTM Model, Training, and Evaluation

A separate LSTM classifier was trained for each Surah. The architecture used a 64-unit LSTM layer with return_sequences=True, dropout of 0.30, a second 32-unit LSTM layer, a 32-neuron ReLU dense layer, and a Softmax output layer whose size matched the number of verses. The design follows the sequential modelling principle of LSTM [28] while keeping the model compact enough for application integration. Table 3 summarises the architecture and training configuration.

Table 3
LSTM Model and training configuration

Component	Configuration
Input representation	MFCC
Input dimension	50 × 13
First recurrent layer	LSTM, 64 units
Return sequence	True
Regularisation	Dropout = 0.30
Second recurrent layer	LSTM, 32 units
Fully connected layer	Dense, 32 units
Dense activation	ReLU
Output layer	Softmax
Output classes	4, 6, or 7 depending on Surah
Loss function	Categorical cross-entropy

Table 3 (***Continued***)

Component	Configuration
Optimiser	Adam
Batch size	8
Early stopping	Validation loss, patience = 5
Restored weights	Best validation-loss weights
Train-test split	80:20
Random state	42
Validation data	20% of training data
Al-Ikhlas training	50 epochs
An-Nas training	20 epochs
Al-Fatihah training	20 epochs

Each dataset was divided into 80% training and 20% testing using random_state=42; 20% of the training portion was used for validation. Models were compiled with Adam and categorical cross-entropy using a batch size of 8. Early stopping monitored validation loss with patience of five epochs and restored the best weights. Al-Ikhlas was configured for up to 50 epochs, while An-Nas and Al-Fatihah were configured for up to 20 epochs. Evaluation used held-out test accuracy and loss together with class-level precision, recall, F1-score, and confusion matrices so that overall and verse-specific behaviour could be examined.

2.3 Mobile Application Integration

The trained classifiers were integrated into the Quranic mobile application. In learning mode, a user selects one of the three Surahs, records a recitation, and submits the audio to the same preprocessing and MFCC pipeline used during model development. The relevant classifier predicts the verse class, after which the application maps the class to Quranic text and highlights the predicted verse. Functionality testing reported successful operation of recitation recording, prediction, and verse highlighting. Within the proposed pedagogy, this interaction supports independent Muraja'ah and may provide preliminary self-checking before formal teacher-led Tasmik; it is not an assessment of Tajwid or pronunciation correctness.

3. Results and Discussion

Model performance differed substantially across the three Surahs. The analysis therefore considers both overall test performance and verse-level confusion, followed by the practical implications of integrating the model into the learning application.

3.1 Overall Verse-Identification Performance

Table 4 shows that Al-Ikhlas achieved the highest test accuracy at 90.21%, followed by Al-Fatihah at 74.83% and An-Nas at 70.75%. The approximately 19-percentage-point gap between Al-Ikhlas and An-Nas indicates that recognition quality cannot be attributed to the architecture alone. Al-Ikhlas had four target classes and 6,024 augmented samples, whereas An-Nas and Al-Fatihah had six and seven classes with fewer samples. These differences, together with verse-specific acoustic similarity, are plausible contributors to the performance gap, although the experiment did not isolate their individual causal effects.

Table 4
Overall performance of the LSTM verse-identification models

Surah	Reported Accuracy	Loss	Test Accuracy	Test Loss
Al-Ikhlas	89.60%	0.2677	90.21%	0.2588
An-Nas	68.92%	0.9128	70.75%	0.8733
Al-Fatihah	74.77%	0.8467	74.83%	0.8313

The similarity between reported accuracy and held-out test accuracy within each Surah suggests that no large deterioration occurred on the test split. Nevertheless, the moderate absolute performance for An-Nas and Al-Fatihah shows that stable generalisation is not equivalent to uniformly reliable recognition. Verse-level analysis is therefore necessary before the model can be interpreted as learner-facing feedback.

3.2 Verse-Level Performance and Error Patterns

Table 5 summarises the strongest and most challenging verse-level findings. Al-Ikhlas was consistently strong: Verse 1 reached precision 1.0000, recall 0.9931, and F1-score 0.9965, while the remaining verses also performed well. Its main confusion was concentrated between Verses 3 and 4, indicating a local rather than system-wide classification problem.

Table 5
Key verse-level classification findings

Surah	Strongest Finding	Most Challenging Finding	Interpretation
Al-Ikhlas	Verse 1: Precision 1.0000, Recall 0.9931, F1 0.9965	Verse 3 showed slightly lower precision of 0.9720	Recognition was consistently high across all four verses
An-Nas	Verse 5: Precision 0.9441, Recall 0.9441, F1 0.9441	Verse 2: Recall 0.6134, F1 0.7104; Verse 3 precision 0.7339	Considerable class-dependent variation
Al-Fatihah	Verse 7: Precision 0.8244, Recall 0.7897, F1 0.8067	Verse 1: Precision 0.6374, Recall 0.6579, F1 0.6475	Several verses remained difficult to distinguish

An-Nas showed greater class-dependent variation. Verse 5 achieved precision, recall, and F1-score of 0.9441, whereas Verse 2 produced recall of 0.6134 and F1-score of 0.7104. The confusion matrix showed frequent confusion between Verses 2 and 3 and smaller error clusters involving Verses 4 and 6. Al-Fatihah showed a similar pattern of non-uniform difficulty: Verse 7 achieved F1-score 0.8067, while Verse 1 achieved 0.6475 and was confused with several other verses. These concentrated errors indicate that some verse pairs are less acoustically separable than others under the current feature representation.

One plausible contributor is the strong phonetic similarity created by repeated verse-end patterns and rhyme-like endings in Quranic recitation. In short Surahs such as An-Nas, several verses contain recurring terminal sounds and closely related rhythmic contours. When verses share similar final syllables, vowel patterns, and recitation cadence, a classifier may assign substantial weight to these common acoustic cues rather than to the earlier phonetic segments that distinguish one verse from another. This can increase confusion between verses whose endings sound similar even when their lexical content differs. A comparable problem can arise in Al-Fatihah, where melodic recitation, sustained vowels, and recurrent phrase-final acoustic patterns may reduce the distinctiveness of verse-level representations.

The use of only 13 MFCC coefficients may further contribute to this limitation. MFCCs provide a compact summary of the short-term spectral envelope and are effective for representing broad acoustic characteristics, but a 13-coefficient representation compresses detailed information about fine phonetic transitions. In the present system, each recording was represented as a 50 x 13 MFCC sequence, so distinctions that depend on subtle consonantal articulation, formant transitions, duration, or other local pronunciation cues may not be fully preserved. This is particularly important when two verses share similar global spectral and prosodic patterns. The LSTM can model temporal dependencies across the MFCC sequence, but it cannot recover discriminative phonetic information that has already been weakened during feature extraction and fixed-length standardisation. Future work should therefore examine richer acoustic representations, including delta and delta-delta MFCCs, higher-dimensional MFCC settings, log-Mel spectrograms, or pretrained speech embeddings, to determine whether finer phonetic differences between similar-sounding verses can be captured more effectively.

The results are consistent with broader Quranic speech-recognition research showing that performance depends on task definition, data diversity, speaker variation, and model architecture [17-24,29]. More advanced systems have used Transformer, CTC/attention, phoneme-based, and large pretrained speech models [21-24], but their transcription or phoneme-recognition objectives are not directly comparable with multiclass verse-identification accuracy. The present findings therefore demonstrate feasibility within a constrained task rather than universal Quranic speech recognition.

Speaker diversity is an important limitation for future deployment. Although the source audio was selected to include variation in voice, accent, rhythm, speed, and tonal characteristics, the dataset did not contain systematic speaker demographic metadata such as age, gender, accent, or recitation proficiency. As a result, the present study cannot determine whether the training data adequately represent different reciter populations or whether performance is consistent across demographic groups. This creates a potential risk of model bias if particular voice characteristics are over-represented in the training data. A model trained predominantly on adult or male voices, for example, may experience reduced accuracy when used by children or female reciters because of differences in pitch range, vocal-tract characteristics, speaking rate, pronunciation, and recitation style. Accent and proficiency differences may introduce additional acoustic variability that was not explicitly measured in the current evaluation. These issues are especially important for a learner-facing Quranic application, where users may differ substantially from the reciters represented in the development data. Previous Quranic speech research has similarly highlighted the importance of gender and speaker-independent evaluation [20,23]. Future datasets should therefore record relevant speaker metadata and include balanced representation across age, gender, accent, and proficiency groups, followed by subgroup-specific evaluation to identify and mitigate performance disparities.

3.3 Application Functionality and Pedagogical Implications

The trained models were successfully incorporated into the mobile application for Quranic text selection, reference-audio playback, learning mode, recording, verse prediction, and highlighting, as summarised in Table 6. This demonstrates end-to-end technical integration from recitation capture to verse-level feedback.

For Muraja'ah, the application enables a practical cycle of recall, recite, recognise, display, review, and repeat. The study demonstrates the technical functionality required for this interaction, but it does not measure whether using the application improves long-term memorisation or learning

outcomes. For Tasmik, the role must remain more limited: recognising a verse is not equivalent to evaluating the correctness or quality of recitation. The 70-75% test accuracies for An-Nas and Al-Fatihah further show why predictions should not be treated as authoritative assessment.

Table 6
Functional integration of the verse-identification model

Function	Intended Operation	Reported Result
Quranic text selection	Display selected Al-Ikhlas, An-Nas, or Al-Fatihah verses	Success
Reference recitation	Play prerecorded audio for selected verse	Success
Learning mode	Present verses for recitation practice	Success
Audio recording	Record and stop learner recitation in real time	Success
Verse identification	Process learner audio and predict corresponding verse	Success
Verse highlighting	Highlight the verse identified by the model	Success

Accordingly, the principal contribution is not an automated Quran teacher, but a verse-identification mechanism that can extend opportunities for independent practice while preserving formal teacher-led verification. Tahsin-oriented functions, including Tajwid, makhraj, and phoneme-level pronunciation feedback, require finer-grained speech analysis and remain outside the present scope.

4. Conclusion

This study developed an MFCC-LSTM approach for Quranic verse identification and integrated the trained models into a mobile learning application. Test accuracy reached 90.21% for Al-Ikhlas, 70.75% for An-Nas, and 74.83% for Al-Fatihah. Verse-level metrics and confusion matrices showed that errors were concentrated within specific verse pairs, demonstrating that recognition difficulty varies by class and is influenced by the available data and acoustic similarity among verses.

The study also demonstrates a pedagogically bounded use of AI in Quranic learning. Automatic verse identification can support independent Muraja'ah and provide a preliminary self-check before formal Tasmik, but it does not assess Tajwid, makhraj, pronunciation quality, or overall recitation correctness. Teacher-led verification therefore remains essential. The successful recording-prediction-highlighting workflow establishes the feasibility of connecting speech classification with a practical learner-facing application.

Future work should extend the dataset to more Surahs and more diverse learner populations, evaluate speaker-independent performance under varied recording conditions, and compare the current lightweight classifier with stronger pretrained or end-to-end speech models. A further direction is Tahsin-oriented analysis at word or phoneme level so that verse identification can eventually be complemented by targeted Tajwid and pronunciation feedback.

Acknowledgement
The authors gratefully acknowledge Universiti Teknologi MARA (UiTM) for the funding support provided through Geran Komuniti TEJA (GKT 2025/1-4), UiTM Cawangan Melaka.

References

[1] bin Yahya, Muhammad Arif, Sabri Mohamad, Muhammad Nur Hakim bin Abd Malik, Saiful Azman Bidin, and Arif Chasanul Muna. "Empowering the tradition of Quran memorization through artificial intelligence (AI): A conceptual and contemporary review." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 447-475. https://doi.org/10.22452/quranica.vol17no2.19

[2] Luthfiah, Salwaa, and Fajar Syarif. "Strengthening Qur'anic Memorization through Muraja'ah and Tasmi'at Daarul Khoir Islamic Boarding School, Bogor." *DAYAH: Journal of Islamic Education* 8, no. 1 (2025): 13-25.

[3] Yusup, N., M. Marzuqi, and A. Rahim. "Murajaah as a Key Strategy in Quranic Retention: Insights from a Mini Review." *Al-Makrifah Journal of Knowledge and Learning in Islamic Tradition and Culture* 3, no. 2 (2025): 16-25. https://doi.org/10.37134/almakrifah.vol3.2.2.2025

[4] Abi Fahmi, Muhamad, Ihsan Mustofa, and Jaenullah Jaenullah. "Implementation of The Tasmi'and Muroja'ah Qur'anic Methods to Instill Learning Motivation and Students' Ability to Memorize The Qur'an." *Assyfa Journal of Islamic Studies* 3, no. 2 (2025): 622-632.

[5] Jaafar, Azhar, and Nur Rasyidah Kamaruzaman. "A systematic literature review (SLR) on Quranic memorization: Benefits, methods, and innovations." *Asian Social Science and Humanities Research Journal (ASHREJ)* 6, no. 2 (2024): 37-49.

[6] Zahra, Wahda Zulfa Inayatuz, Luluk Ifadah, and Mohamad Ardin Suwandi. "Optimizing juz 30 memorization through traditional qur'anic methods: Tasmi'and muroja'ah at baitul huda." *Amorti: Jurnal Studi Islam Interdisipliner* (2025): 63-68. https://doi.org/10.59944/amorti.v4i2.372

[7] Haryono, Kholid. "Quran memorization technologies and methods: Literature review." *IJID (International Journal on Informatics for Development)* (2023). https://doi.org/10.14421/ijid.2022.3746

[8] Saad, Mohd Faizulamri Mohd, and Safinah Ismail. "Traditional to digital: Evaluating the use of AI in the Tarteel application to enhance Quran memorization." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 53-73. https://doi.org/10.22452/quranica.vol17no2.3

[9] Nasir, Khairulnazrin, Rahim Kamarul Zaman, Ahmad Bazli Ahmad Hilmi, Abdul Hakim Mahadzir, and Ahmad Mukhlis bin Mustaffa. "Artificial intelligence integration in mobile applications: Innovation and challenges in supporting Quran memorization and review." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 612-645. (2025). https://doi.org/10.22452/quranica.vol17no2.24

[10] Ahmad, Khalilullah Amin, Wafa Abdul Jabbar Shohibuddin, and Amir Adel Mabrouk Eldeib. "Artificial Intelligence (AI) In Quranic Education: A Systematic Review Of Pedagogical Applications And Challenges." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 187-213. https://doi.org/10.22452/quranica.vol17no2.8

[11] Zainadun, Nuruliza, Muhamad Nasir Mohamad Salleh, Asyraf Isyraqi Jamil, Abd Aziz Rekan, and Muhammad Talhah Ajmain. "Exploring the potential of artificial intelligence in enhancing Quranic teachers' pedagogy: A systematic literature review." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 501-541. https://doi.org/10.22452/quranica.vol17no2.21

[12] Ab Alim, Nik Nurul Akmal, Khairussaadah Wahid, Siti Nor Haliza Abd Zamani, and Faezy Adenan. "Artificial intelligence as a support tool for Quran memorization: An exploratory study on the potential use of AI applications among non-Islamic studies students." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 157-186. https://doi.org/10.22452/quranica.vol17no2.7

[13] Aisyah, A., A. N. Utami, T. Nafiah, Y. S. Zhahira, and A. Nurrohim. "Pemanfaat Aplikasi Digital dalam Pembelajaran Al-Qur'an: Studi Komparatif Aplikasi Tarteel dan Qur'an Indonesia untuk Murojaah Mandiri." Jurnal Pendidikan Tambusai 9, no. 3 (2025): 37747-37757.

[14] Yusof, Raja Jamilah Raja, Muhamad Alihanafiah Norasid, Mustaffa Abdullah, Nasrul Ariff Ashraf Nasaruddin, NurulAin Badrol Hisham, Ali Ali Gobaili Saged, and Abdollatif Ahmadi Ramchahi. "Digital Al-Qur'an Applications and Artificial Intelligence (AI): An Overview." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 646-676. https://doi.org/10.22452/quranica.vol17no2.25

[15] Syahir, Aminun Nabil Ahmad, Mohd Syukri Zainal Abidin, Che Zarrina Sa'ari, and Muhamad Zulfadli Abdul Rahman. "Artificial intelligence and digital transformation in Qur'anic studies: A systematic literature review." *QURANICA-International Journal of Quranic Research* 17, no. 2 (2025): 542-585. https://doi.org/10.22452/quranica.vol17no2.22

[16] Mahfud, Ahmad, Nurul Hamidah, Surya Saputra Mahmud, and Abd Kholid. "Mengintegrasikan AI dalam Pembelajaran Al-Qur'an: Analisis Potensi, Tantangan, dan Solusi." *Tadabbur: Jurnal Integrasi Keilmuan* 4, no. 1 (2025): 63-72. https://doi.org/10.15408/tadabbur.v4i1.46178

[17] Besdouri, Fatma Zahra, Inès Zribi, and Lamia Hadrich Belguith. "Arabic automatic speech recognition: challenges and progress." *Speech Communication* 163 (2024): 103110. https://doi.org/10.1016/j.specom.2024.103110

[18] Al-Shidi, Alia, Farah Hani Bt Nordin, Izzeldin I. Mohamed, M. A. Younis, Imadeldin Elsayed Elmutasim, and Eimad Eldin Abusham. "A literature review on natural language processing techniques for Qur'anic studies: challenges and insights." *Frontiers in Signal Processing* 5 (2025): 1535166. https://doi.org/10.3389/frsip.2025.1535166

[19] Osman, Hanaa Mohammed, Ban Sharief Mustafa, and Yusra Faisal. "QDAT: A data set for reciting the Quran." *International Journal on Islamic Applications in Computer Science And Technology* 9, no. 1 (2021).

[20] Al-Issa, Suhad, Mahmoud Al-Ayyoub, Osama Al-Khaleel, and Nouh Elmitwally. "Towards building a speech recognition system for Quranic recitations: A pilot study involving female reciters." *Jordan Journal of Electrical Engineering* 8, no. 4 (2022): 307-321. https://doi.org/10.5455/jjee.204-1612774767

[21] Hadwan, Mohammed, Hamzah A. Alsayadi, and AL-Hagree Salah. "An end-to-end transformer-based automatic speech recognition for qur'an reciters." *Computers, Materials and Continua* 74, no. 2 (2022): 3471-3487. https://doi.org/10.32604/cmc.2023.033457

[22] Alfadhli, Sumayya, Hajar Alharbi, and Asma Cherif. "qArI: A hybrid CTC/attention-based model for Quran recitation recognition using bidirectional LSTMP in an end-to-end architecture." *IEEE Access* 12 (2024): 95762-95777. https://doi.org/10.1109/ACCESS.2024.3425273

[23] Al-Zaro, Samah, Mahmoud Al-Ayyoub, and Osama Al-Khaleel. "Speaker-independent phoneme-based automatic quranic speech recognition using deep learning." *IEEE Access* 13 (2025): 125881-125896. https://doi.org/10.1109/ACCESS.2025.3589252

[24] Alshboul, Mohammad, Abdul Rahman Al Muaitah, Suhad Al-Issa, and Mahmoud Al-Ayyoub. "Enhanced neural speech recognition of Quranic recitations via a large audio model." *Applied Sciences* 15, no. 17 (2025): 9521. https://doi.org/10.3390/app15179521

[25] Davis, Steven, and Paul Mermelstein. "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences." *IEEE transactions on acoustics, speech, and signal processing* 28, no. 4 (1980): 357-366. https://doi.org/10.1109/TASSP.1980.1163420

[26] Samara, Ghassan, Essam Al-Daoud, Nael Swerki, and Dalia Alzu'bi. "The recognition of holy qur'an reciters using the mfccs' technique and deep learning." *Advances in Multimedia* 2023, no. 1 (2023): 2642558. https://doi.org/10.1155/2023/2642558

[27] Saber, Hebat-Allah, Ahmed Younes, Mohamed Osman, and Islam Elkabani. "Quran reciter identification using NASNetLarge." *Neural Computing and Applications* 36, no. 12 (2024): 6559-6573. https://doi.org/10.1007/s00521-023-09392-1

[28] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9, no. 8 (1997): 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

[29] Nigar, Natasha, Amna Wajid, Sunday Adeola Ajagbe, and Matthew O. Adigun. "An intelligent framework based on deep learning for online Quran learning during pandemic." *Applied Computational Intelligence and Soft Computing* 2023, no. 1 (2023): 5541699. https://doi.org/10.1155/2023/5541699