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Techniques of Quran reciters recognition: a review

Ibrahim Ahmed Al-Omari, Asma Al-Shargabi, Mohammed Hadwan
Department of Information Technology, College of Computer, Qassim University, Buraydah, Saudi Arabia

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ABSTRACT

The Quran is the holy book of the Islam. Reading and listening to the Quran is an important part of the daily life of Muslims. Muslims are keen to listen to recitations of Quran by skilled reciters to learn the correct recitation for the purpose of understanding and contemplating. Therefore, there are large variety of audio recitations for many skilled reciters. With the availability of this huge amount of recitations and also with the great progress in voice recognition technologies, many research efforts have been devoted to contribute making recitation better using artificial intelligence. One useful application in this area is identifying the reciters of the Quran. There are various solutions introduced by researchers; however, these solutions vary significantly in terms of accuracy, and efficiency. This research seeks to provide a review of these solutions. It also reviews available datasets using different criteria. Finally, some open issues and challenges were addressed.

Corresponding Author:

Asma Al-Shargabi
Department of Information Technology, College of Computer, Qassim University
Buraydah 51452, Saudi Arabia
Email: as.alshargabi@qu.edu.sa

1. INTRODUCTION

The Quran, the holy book of Islam, holds unparalleled significance in both linguistic and religious contexts. Renowned for its eloquence, clarity, and rhetorical mastery, the Quran is revered as the highest Arabic literary work. It is meticulously divided into 30 parts, each named after the chapter (surah) it begins with, encompassing a total of 114 chapters. These chapters collectively contain 6,236 verses and 323,670 letters. Notably, the longest chapter is Al-Baqarah, with 286 verses, while the shortest is Al-Kawthar, with just 3 verses [1]. The Quran is recited using a specialized method known as “Tajweed,” which encompasses a set of rules for correct pronunciation during recitation [2]. Tajweed ensures that each word is articulated accurately, as mispronunciation can significantly alter the meaning of the verses [3].

Speaker recognition technology has revolutionized the way Quranic recitations are cataloged and accessed. By leveraging advanced algorithms to analyze the unique vocal characteristics of individual reciters, this technology is instrumental in categorizing and arranging Quranic recitations or enabling users to search for recitations based on their preferred reciters [4]. Educational institutions and academics derive valuable benefits from this technology, as it facilitates the study and teaching of Tajweed by offering precise identification of reciters and credible examples for educational use. The precise identification helps in ensuring that students learn the correct pronunciation and intonation, preserving the integrity of Quranic recitation.

Furthermore, the preservation of diverse recitation styles is supported, ensuring that the rich oral tradition of Quranic recitation is maintained for future generations. By cataloging various recitation styles, from different regions and dialects, the technology helps in preserving the cultural and linguistic diversity within the Muslim community. This preservation is vital for maintaining the authenticity and richness of the Quranic recitation tradition.

In addition, automatic speech recognition (ASR) systems contribute to the efficient transcription and indexing of Quranic verses [5], streamlining the search for specific verses or chapters. These technological advancements have made Quranic recitations more accessible to a wider audience, including individuals with disabilities or those who prefer digital formats. ASR technology ensures that visually impaired individuals can access accurate audio recitations, while digital formats allow for convenient access on various devices. This enhanced accessibility not only improves the overall user experience but also fosters a deeper connection with the sacred text, allowing more individuals to engage with the Quran in a meaningful way.

The techniques used to recognize Quran reciters encompass a variety of methods and algorithms, particularly in the feature extraction and classification stages [6]. Techniques such as Mel-frequency cepstral coefficients (MFCCs) and deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are commonly employed to achieve high accuracy in reciter recognition. Recent advancements in artificial intelligence have further refined these systems, making them more robust and reliable.

For instance, Tantawi *et al*. [7] developed a large-vocabulary speaker-independent ASR system for Quranic recitations, achieving promising results with a word error rate (WER) ranging from 0.27% to 6.31%. Additionally, Ghori *et al*. [8] explored acoustic modeling using deep learning for Quran recitation assistance, demonstrating the potential of these techniques in improving recognition accuracy. These developments not only facilitate more efficient categorization but also provide users with a personalized and enriched experience when engaging with the Quran. Moreover, the integration of speaker recognition and ASR technologies in Quranic recitation has had a profound impact on accessibility, education, and preservation [9]. By harnessing the power of advanced algorithms and machine learning, these technologies ensure that the Quranic recitation tradition remains vibrant and accessible to all, while also pushing the boundaries of what is possible in the field of speech recognition.

This paper reviews the methods used for Quran reciter recognition and the datasets available in this field. Additionally, it summarizes key insights and strategies that can enhance the accuracy and effectiveness of these recognition systems. The subsequent sections of this paper are meticulously delineated as follows: section 2 devoted to introduce a general view of speaker recognition systems and how it works. Section 3 outlines the research methodology employed in this review, detailing the approach taken. In section 4, reciters recognition techniques are examined, presenting a review of key solutions proposed by the research community for recognizing Quran reciters. Section 5 offers a brief summary of available Quranic recitations datasets. Section 6 presents a discussion and open issues, analyzing the literature and addressing current challenges and unresolved questions. Finally, section 7 concludes with a summary of the work introduced, highlighting key conclusions and suggesting directions for further research.

2. OVERVIEW OF SPEAKER RECOGNITION SYSTEMS

Speaker recognition is one of the most important uses of voice recognition systems. Speaker recognition aims at determining who is speaking in a given speech by matching the voice biometrics of the speaker's voice, the voice biometrics pattern is learned by training [2]. As a result of variations in vocal tract form and larynx volume, each person's voice is distinctive. Every speaker has a unique feature of speaking, which may include rhythm, tone, a pattern of pronunciation, or others [10]. Speaker recognition methods have utilized these unique features to produce accurate solutions. As shown in Figure 1, speaker recognition systems typically include many phases; the main ones are pre-processing, feature extraction, model training, and recognition [11]. Many researchers have used various extraction methodologies and classification techniques to recognize the speakers with remarkable results, for instance, the hidden Markov model (HMM) [12]–[15], Gaussian mixture model (GMM) [16], [17], artificial neural network (ANN) [18], K-nearest neighbor (KNN) and support vector machines (SVM) [19]. Furthermore, feature extraction is essential since it can significantly boost the efficiency of the model by making the data more useful and lowering its dimensionality. MFCC [20] and linear predictive coding (LPC) [19] are the most popular acoustic feature extraction methods. Despite recent improvements in speaker recognition, there are still many challenges such as variability and a lack of data [21], section 6 introduces a detailed discussion and highlights the main challenges and open issues. The following sections discuss the main phases.

2.1. Pre-processing

Pre-processing is an essential stage in producing an accurate speaker recognition system due to a number of factors. Noise is one of the most important factors due to the poor quality of speech and audio recording systems and devices [22]. In addition, the speech signals normally contain numerous periods of silence. The silence signal is meaningless since it contains no information. Zero crossing rate (ZCR) and short-time energy (STE) are two ways to eliminate these periods [23]. Furthermore, the pre-emphasis of the speech signal is essential for high-frequency preprocessing.

It is often used to enhance high-frequency parts of the signal. This entails applying a high-pass filter (FIR) to the signal to enhance the higher frequencies and reduce the lower frequencies [24]. Additionally, in signal processing, the normalization technique is used to ensure that the signal has an accordant level. Normalization decreases the impact of signal gaps as well. Windowing are also signal-processing techniques that are employed to minimize the impact of signal gaps [25]. It includes normalizing the signal to a specific level, splitting it into interfering segments, and then performing a window function on each segment to decrease gaps at the edges.

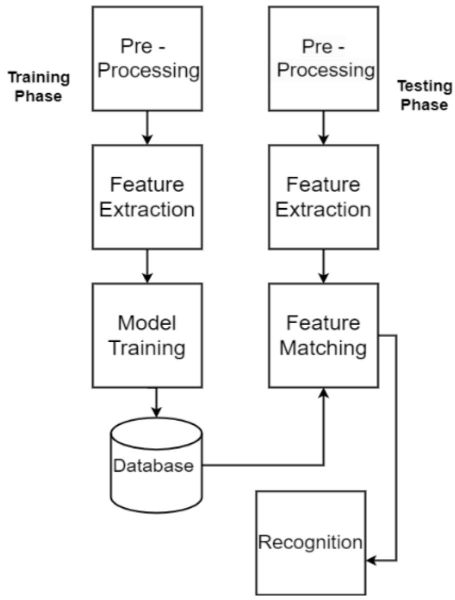

Figure 1. Speaker recognition system framework [26]

2.2. Feature extraction

In speaker recognition, feature extraction is the technique of extracting significant features from audio signals that might be utilized to recognize a speaker. To better understand a speech signal, it can be broken down into its constituent parts, which is what feature extraction is intended to do. Primarily due to the fact that acoustic signals include an overwhelming amount of data, much of which is unnecessary for the recognition process [27]. The extraction of audio features involves the alteration or processing of audio signals by transforming digital and analog signals, reducing undesirable noise, and optimizing the time-frequency ranges [28]. There are multiple ways to parameterize and express the voice signals for the detection process. The main used methods are MFCC and LPC. Table 1 shows a comparison of MFCC and LPC.

Table 1. Comparison of MFCC and LPC

Feature/technique	MFCC	LPC
Basis	Filter bank coefficients	Modeled by all Pole model
Filtering features	Mel-scale	Source-filter model
Advantages	High accuracy	High speed
Disadvantages	Sensitive to background noise	Highly sensitive to quantizing noise

MFCC is the most commonly utilized feature extraction technique for speech and audio processing [29]. It is widely employed in speech recognition systems as a way to represent the signal's spectral content. The MFCC is a concise representation of a signal's spectral content expressed as a collection of coefficients. The MFCC has its basis in the sensitivity of the human hearing mechanism to frequency changes in a signal [30]. In general, the fundamental steps for calculating MFCCs are frame blocking, which involves dividing the signal into short frames, and windowing, which requires applying a window function to each frame to minimize spectral leakage [31]. Following that, apply the fast fourier transform (FFT) to calculate the discrete fourier transform (DFT) of each windowed frame to acquire representations in the frequency domain. Subsequently, utilize a Mel filter bank (Mel frequency wrapping) to process the power spectrum by converting the frequencies to the Mel scale and subsequently implementing triangle filters. Once the computations for the Mel filter bank outputs have been completed and their logarithm has been calculated, the resulting energies are decorrelated using the discrete cosine transform (DCT). This process generates a set of coefficients referred to as cepstral coefficients. Figure 2 shows the MFCC block diagram.

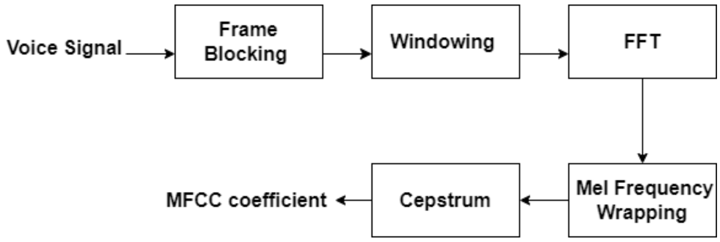

Figure 2. MFCC block diagram [32]

In addition, LPC is a common method for processing audio signals, notably speech. In the field of voice signal compression, it has proven very useful, allowing for extremely high compression rates. LPC simulates the human vocal tract by modeling the spectral envelope of a digital speech signal with a mathematical model [33], [34]. The initial steps of computing LPC are similar to MFCC which include: frame blocking and windowing. After that, autocorrelation analysis involves calculating the autocorrelation function of the windowed frame [27]. Subsequently, the LPC analysis process converts each autocorrelated frame into a set of LPC parameters, which are LPC coefficients. Figure 3 shows the LPC block diagram. For auditory modeling, LPC and MFCCs have mostly employed features. Based on the prior sampling, LPC makes predictions about future values. While the MFCC takes into account the speech's nature during feature extraction [35].

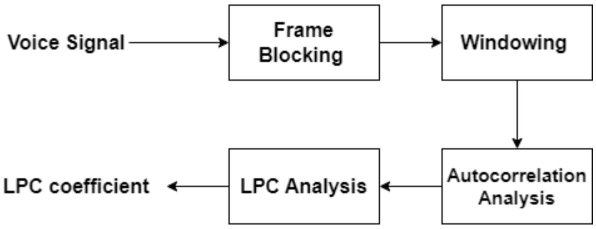

Figure 3. LPC block diagram [36]

2.3. Modeling and recognition

After feature extraction, the next step is to model the speakers. The objective of modeling approaches is to generate speaker models that facilitate the process of feature matching for the goal of identifying the speaker's voice [37]. There are different modeling methods. The classical approaches include vector quantization (VQ) [38], dynamic time wrapping (DTW) [39], GMM [40], and HMM [41]. Machine learning techniques are also utilized such as SVM [42] and ANN [43]. Hybrid approaches incorporate two or more of the previous techniques are also used in the literature such as what introduced in [44] that employs both ANN and HMM.

3. RESEARCH METHODOLOGY

This study is achieved by following these major steps: i) identifying the problem, and the related research questions, ii) developing the keywords for the search, iii) defining the document databases and the inclusion and exclusion criteria, iv) searching the document databases, v) defining the data to be extracted from the documents identified, vi) recording the data, and vii) synthesizing and reporting the results. The main steps are described as follows. The problem statement is illustrated in section Introduction, and the related questions can be covered with these following questions, as shown by Table 2.

Table 2. Research questions

No.	Research question
Q1	What are the publicly available databases/datasets of Quranic recitations, and how do these datasets differ in quality?
Q2	What are the features extraction techniques that used to define reciters features, and how they affect the accuracy of reciters recognition techniques?
Q3	What are the techniques that used to recognize/determine/classify Quran reciters, and how they affect the accuracy?
Q4	What are the challenges of recognizing Quran reciters techniques?

These questions are identified due to the nature of the Quran reciters recognition process where the key factors of recognizing process are twofold: i) the feature extraction technique, and ii) the recognizing technique. On the other hand, the quality of the results is affected by the quality of the data in terms of its size, diversity, and comprehensiveness. Therefore, studying the datasets that used in previous studies and analyzing the impact of its quality on the quality of the results and identifying the reasons for that would contribute to clarifying one of the most important reasons affecting the quality of the solution in general. Finally, identifying the challenges facing researchers in this field will contribute to directing researchers' efforts and clarifying proposed research paths in the future.

Answering all the questions and specifying their details will contribute to clarifying the factors affecting the quality of the models used to identify Quran reciters and build high-accuracy models, and then generalizing the results scientifically. In addition, specific criteria were used to evaluate and classify the collected publications to be included or excluded in this study; Table 3 illustrates these criteria. The most of included publications were journal papers as shown in Figure 4. Figure 5 depicted that a limited number of research papers have been published between 2012 and present in this area. The lack of research in this area opens the door for researchers to focus more on the use of emerging technologies, AI and deep learning techniques in this vital area.

The different research questions are systematically addressed in the following sections. Section 4 examines questions Q1 and Q2. While section 5 delves into Q1. Section 6 focuses on Q4 and provides a comprehensive analysis of all findings.

Table 3. Inclusion and exclusion criteria for collected publications

Criteria	Area of interest in publication
Inclusion	– Utilize speaker recognition for Quranic recitation – Recognizing Quran reciter – Recognizing Quran recitation style
Exclusion	– Publications without experimental results. – Not published in the English language

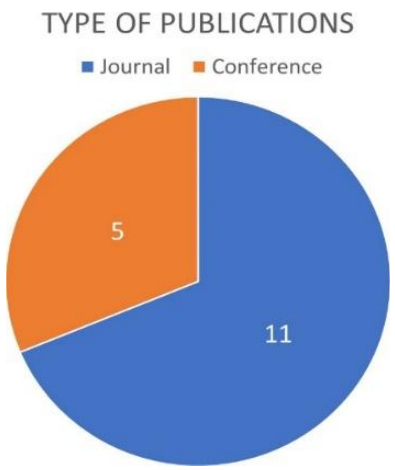

Figure 4. Type of publications

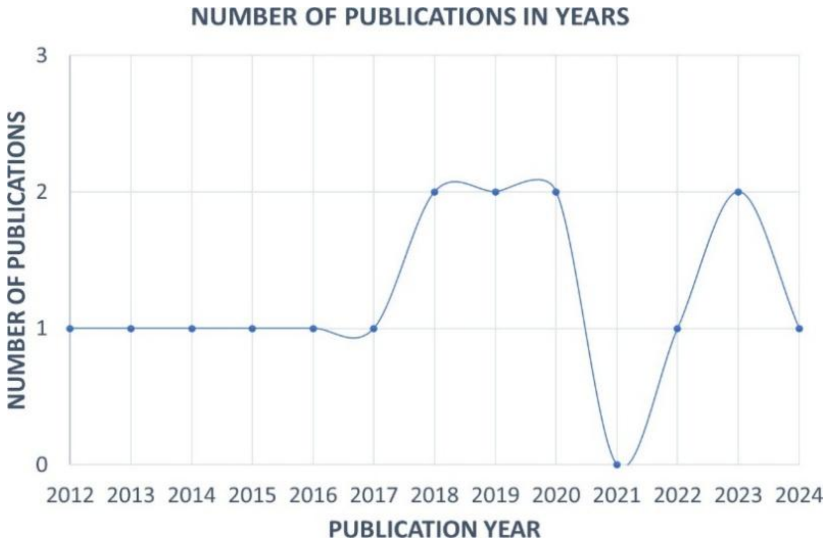

Figure 5. Number of publications in years

4. RECITERS RECOGNITION TECHNIQUES

Several studies have been published to enhance and improve Quranic reciter recognition systems. In addition, a range of approaches and classification techniques were employed and evaluated, as shown in Figure 6. This section explores the existence of literature that is divided into three subsections according to categorization: traditional, machine learning, and deep learning methods.

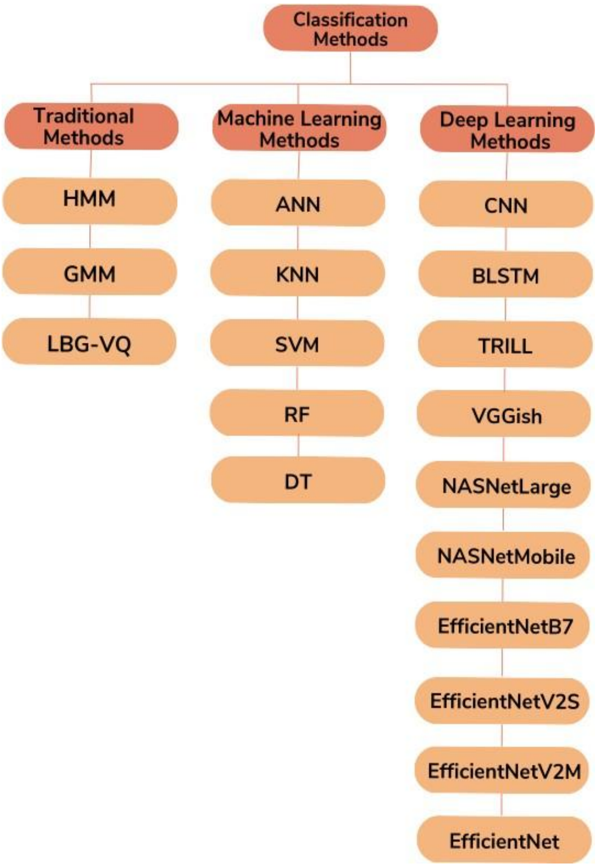

Figure 6. A summary of classification methods used for recognizing Quran reciters

4.1. Traditional methods

Khelifa *et al*. [13] developed an effective ASR-based Quranic sound recognition system to recognize and identify Quranic sounds. The first phase starts with a baseline HMM based system for fundamental Quranic sounds. The second phase improves this baseline system using Quranic sound duration modeling techniques. Gamma, Gaussian, and Poisson distributions were examined and incorporated into HMM training and decoding to model state durations. The proposed modeling techniques have improved the results significantly with 99% accuracy.

Moreover, Baig *et al*. [45] presented a Quranic recitation system that recognizes recitation on a phoneme basis. For audio models, minimum phone error (MPE), and machine learning, accordingly, non-discriminative and discriminative training methods are used and evaluated. MPE minimizes phone errors to produce better results with an 85% accuracy rate. MPE generalizes unseen data better than machine learning. MPE outperforms machine learning when trained and tested on noisy datasets.

Likewise, a technique for identifying Quranic reciters was presented by Gunawan *et al*. [16]. The GMM classifier and MFCC features were used. Using fifteen samples from each of the five reciters, they build an audio database of the Quran for the experiment. ten were utilized for training purposes and five for testing. In addition, they employ an additional unknown reciter to assess the effectiveness of the proposed system. During the training and testing phase, the proposed system demonstrated 100% accuracy, based on the results. 100% rejection rate was also reached for unknown samples.

In a different context, Hammami *et al*. [46] advanced a system that can reply to user voice requests by reciting a portion of the Quran in line with the user input. The system aims to enable user exploration and navigation between Quranic verses or pages using voice recognition of Arabic numerals. The system is useful for those who are blind or visually impaired. GMM is used with MFCC as a classifier. The proposed solution achieved a 99.31% accuracy rate.

Al-Jarrah *et al.* [47] proposed an enhanced Linde–Buzo–Gray (LBG) algorithm for recognizing Holy Quran reciters. The original LBG algorithm is an iterative VQ algorithm to improve a small set of vectors (codebook) to represent a larger set of vectors (training set), such that it will be locally optimal. The codebook is a compressed representation of the original data. The basic idea of LBG is to divide the group of training vectors and use it to find the most representative vector from one group. These representative vectors from each group are gathered to form the codebook. The enhanced algorithm that proposed in [47] is a method to align the centroids of codebooks more accurate than the original LBG. The signals were derived from voices of 14 expert reciters. The reciters mainly recited from Surah “Al-Kawthar” for this purpose. The proposed algorithm achieved high level accuracy with 98.21.

As a way to determine who recites the Holy Quran, this study presents a reciter recognition system [48]. For reciter classification, the MFCC analysis and LBG-VQ were used. The proposed approach has the potential to identify the Holy Quran reciter in both live-streamed and recorded broadcasts. A database containing 200 samples, comprising recordings made by 20 reciters, was utilized in the experiment. The results show that for clean samples, a recognition rate of 86.5% has been achieved.

4.2. Machine learning methods

Alkhateeb [49] introduced a model based on ANN and KNN as classifiers, MFCC is used for feature extraction. Using the ANN, the proposed system gives 97.62% accuracy for chapter 18 and 96.7% accuracy for chapter 36. On the other hand, the proposed system gives 97.03% accuracy for chapter 18 and 96.08% accuracy for chapter 36 by using the KNN.

Asda *et al.* [18] designed a system that can identify the speaker’s voice as a unique biometric signal to recognize the reciter. This research used ANN and MFCC for feature extraction. The mismatch error rate has decreased by retraining the network and increasing the size of the hidden layer. The results achieved 91.2% accuracy. Nahar *et al*. [50] investigated the recognition of Quran reciters using SVM and ANN. This research used a corpus contains ten recitation types. The results demonstrated that the best results have been achieved using SVM with 96% accuracy.

A Holy Quran reciter identification system that utilizes sound waves to represent the pronunciation of verses was introduced in [51]. After features extractions using MFCC, SVM, and ANN used individually to identify the reciter. The obtained findings demonstrate that the SVM outperformed the ANN with 96.59% accuracy rate.

Shah and Ahsan [52] used a combination of LPC and discrete wavelet transform (DWT) for feature extraction. Random forest (RF) classifier is used. According to the study, training the RF classifier using LPC or DWT separately reduced the accuracy, while training using features extracted by both LPC and DWT improved the recognition accuracy. The results achieved 90.90% accuracy rate.

A novel approach for recognizing Holy Quran reciters was introduced in [53]. The authors used two different techniques for audio representation. The first one is the audio signal in the frequency domain. The second one was considering the audio as images by utilizing the Spectrogram. Three classifiers, including naïve Bayes (NB), J48, and RF, were employed to effectively learn the distinction between classes. A database of 120 audio files of Quranic recitations from 12 different reciters was utilized. The results indicated that the highest level of accuracy, with 88%, was achieved using RF classifier and by using the audio signals for representing the data.

4.3. Deep learning methods

Qayyum *et al.* [54] leverage the power of RNN abilities for evaluating and modeling sequential speech data, namely bidirectional long short-term memory (BLSTM). As input, the model was given recitations from five well-known reciters. MFCC is used for feature extraction. Several recitation lengths and performance indicators were utilized to carry out a comparative analysis of BLSTM in conjunction with various baseline classifiers. Based on the findings, BLSTM was better with 99.89% accuracy than other common deep neural networks (DNNs) in terms of their ability to represent the temporal dynamics of Quran recitations.

A deep learning model that can distinguish between authentic and false Quran recitations was presented in [55]. The proposed solution achieved a remarkable accuracy rate with 99.66%. The results also demonstrated that the deep learning proposed model outperformed the classical machine learning methods on the same dataset. The proposed model was utilized to conduct several comparisons of segment length and feature number to identify the ideal values that would result in the maximum achievable accuracy. The experimental findings indicate that a segment length of 4 seconds and a feature count of 30 yield excellent results.

Tall *et al*. [56] introduced an innovative approach utilizing deep learning techniques to recognize the reciter, sura, and verse of a Quranic recitation. Furthermore, they demonstrated the efficacy of employing pre-trained embedding models to categorize various reciters. Moreover, they indicated that the approach achieved remarkable precision in recognizing the reciter of a provided passage. The experimental dataset was acquired from multiple open-source platforms. Additionally, a class comprising irrelevant sounds, such as music or discussion, was appended to the reciters to prevent the model from misclassifying an unrelated sound as a reciter. The experiments achieved an excellent result by using the TRIpLet loss network (Trill) model, which reached an accuracy of 98%.

Saber *et al.* [57] proposed an approach utilizing deep transfer learning models to recognize a Holy Quran reciter. The proposed approach evaluates six pre-trained deep learning models that have been incorporated separately. Furthermore, a dataset of the Holy Quran is constructed by converting audio files into image-based visual representations using MFCC features extracted from 11,000 audio files. The dataset includes recordings from 20 different reciters. Along with the pre-trained models, NASNetLarge achieved the best accuracy rate of 98.50% according to the result. Table 4 provides a summary of research papers that explored the recognition of Quran reciters.

Table 4. Summary of techniques used in Quran reciters recognition studies

Ref.	Year	Classification technique	Dataset	Features extraction technique	Best accuracy rate
[48]	2012	LBG-VQ	200 samples from 20 reciters	MFCC	86.5%
[46]	2013	GMM	-	MFCC	99.31%
[52]	2014	RF	96 audio samples from 6 reciters	DWT, LPC	90.90%
[45]	2015	HMM	-	MFCC	85%
[18]	2016	ANN	Quranic recitation from 5 different reciters	MFCC	91.2%
[13]	2017	HMM-GMM	5935 audio samples from 10 reciters	MFCC	99%
[16]	2018	GMM	15 audio samples from 5 reciters	MFCC	100%
[54]	2018	KNN, RF, DT, LR, SVM, BLSTM	Quranic recitation from 5 different reciters	MFCC	BLSTM=99.89%
[53]	2019	NB, J48, RF	120 samples from 12 reciters	MFCC	RF=88%
[51]	2019	SVM, ANN	Corpus of 15 different reciters	MFCC	SVM=96.59%
[50]	2020	SVM, ANN	Corpus of 10 different reciters	MFCC	SVM=96%
[49]	2020	KNN, ANN	Corpus of 10 different reciters	MFCC	ANN=97.62%
[47]	2022	LBG-VQ	Samples from14 reciters	MFCC	98.21%
[55]	2023	CNNs	Samples from 7 reciters	MFCC	99.66%
[56]	2023	TRILL, VGGish	170 samples from different reciter	MFCC	Trill=98%
[57]	2024	NASNetMobile, NASNetLarge, EfficientNetB7, EfficientNetV2S, EfficientNetV2M, EfficientNetV	11 K samples from 20 reciters	MFCC	NASNetLarge=98.50%

5. QURANIC DATASETS

In a system designed for the recognition of Quranic reciter, the data may be obtained by either the recording of individual recitations or sourced from a pre-existing corpus of standardized Quranic recitations [14]. The waveform audio file format, generally referred to as .wav, is the major audio format preferred by researchers. A proper choice of data is necessary for any reciter recognition system to decrease the time required for additional pre-processing. Many researchers rely on traditional and native language databases, depending on the needs of the study topic. Particular requirements must be met when selecting a database for a reciter recognition system.

As clarified in section 4, it was observed that several studies mention the use of specific datasets for their research. However, detailed sources or references for these datasets were not consistently provided. Due to the distinctive character of Quranic recitations, a few datasets of Quranic recitations have been collected and published in the past few years. These datasets can be used for various tasks, including but not limited to ASR. Most of the available Quranic audio datasets are just folders of audio files, that may need a lot of pre-processing before they can be employed in data-driven development. Table 5 presents a comparison of some publicly available datasets.

6. DISCUSSION AND OPEN ISSUES

This section introduces a discussion about what has been introduced in sections 4 and 5. It also highlights some research gaps and open issues in the field. Starting with datasets, as they are the basis that the different processing phases built upon. As shown in section 5 and Table 5, there are few datasets available and it suffers many problems that make it not suitable for solid experiments. Some of these problems addressed are: the limit size, the number of reciters did not exceed 20 reciters in the best dataset, reciters almost were Arabic reciters, and some studies collect the data based on individual effort for some volunteer reciters who are not highly skilled. In addition, there is no diversity of representation formats, no involving a reasonable amount of noise, and no including various lengths of audio files. Therefore, a major institutional effort is needed to build high-quality Quran audio datasets that are suitable for scientific research purposes and suitable for the use of modern and emerging computing technologies such as training learning and deep learning algorithms. The size, diversity, and different methods of representing audio data, as well as the inclusion of different types of noise, should be taken into account when constructing this type of dataset so that we can say that this data is a representative sample suitable for applying scientific methodologies and achieving honest results without bias.

Table 5. Comparison of available datasets

Name	Format	Number of files	Ref.
Quran.com audio	MP3	1368	[58]
QDAT	wav	1500	[59]
Quran recitations for audio classification	wav	6688	[60]
The tarteel dataset	MP3	25,000	[61]
Holy Quran dataset	wav	200	[62]

Regarding the feature extraction methods, the majority of studies utilized MFCC, as highlighted in Table 4. Conducting in-depth experimental research on other feature extraction methods, particularly modern techniques such as those used in deep learning, and applying them to diverse and extensive datasets, would likely yield more accurate results. Lightweight models could be proposed by excluding non-significant features and tailored models for Quran recitation could be introduced.

In addition, this review revealed several significant findings regarding the classification phase introduced in various literature. Traditional techniques such as HMM, GMM, and LBG-VQ demonstrated impressive results with small datasets but showed low accuracy with larger datasets. This aligns with findings from previous studies [16], [46]–[48]. In contrast, machine learning techniques like SVMs [50], [51] and RF [53] achieved good results; however, when these techniques were evaluated alongside deep learning algorithms on the same datasets, their performance deteriorated compared to deep learning models such as long short-term memory (LSTM) [54]. This observation suggests that deep learning algorithms may offer superior performance in larger, more complex datasets, a trend noted in other comparative studies, although such studies are still limited. Conducting extensive comparative studies using emerging in artificial intelligence, such as complex deep learning models, transfer learning, and hybrid frameworks and optimization methods, would make a significant difference in results based on a solid scientific methodology, as suggested by the current limited studies in this field [57].

Furthermore, there is significant overlap and dependency between the three issues: the quality of the datasets, the methods used to extract features, and the classifiers used to identify the Quran reciter. However, the most important factor as a preliminary step is to work hard to create large and diverse datasets for a large number of reciters around the world. Once available to the research community, these datasets would allow for comprehensive studies and the generalization of results based on a robust scientific foundation. On the other hand, the methods used for data pre-processing are not covered in this study as we did not find a sufficient information in previous literature.

Considering all that has been presented above, as well as what was missing in previous studies, some research challenges and recommendations can be reached that can be summarized as follows:

– A major institutional effort is needed to build high-quality Quran audio datasets. Some key criteria should be identified to create these datasets such as size, diversity, and multi-modal data, as well as the inclusion of different types of noise.
– Conducting extensive comparative studies using emerging technologies in artificial intelligence, deep learning models, transfer learning, and hybrid frameworks and optimization methods.
– Conducting in-depth experimental research on other feature extraction methods, particularly modern techniques such as those used in deep learning (end-to-end techniques), and applying them to diverse and extensive datasets, would likely yield more accurate results. Lightweight models could be proposed by excluding non-significant features and tailored models for Quran recitation could be introduced.
– The efficacy of deep learning, specifically CNNs, RNNs, and LSTM in voice recognition has been substantial. However, there is a need to algorithms that are tailored to address the unique difficulties encountered in Quranic recitation, such as the diverse range of styles and intonations.
– Focusing on data pre-processing methods especially noise pre-processing, data segmentation, representation, and transformation still a very important issue that could be tackled by researchers in this field.
– Conducting several experimental studies using all previous factors would result with introducing a robust tailored framework for Quran reciters recognition.

Finally, we believe that establishing the computational resources using a scientific approach and making them available for all researchers' audiences is the first step for any serious attempts to improve the performance of and the results in this area.

7. CONCLUSION

This paper provides a comprehensive review of the Quran reciter recognition system. The main methods of feature extraction and classification techniques are discussed. Besides, A review of available datasets is introduced. An analytical discussion is also provided to highlight the main gaps and potential open issues. It can be said that the main conclusion of this study is that to develop an effective system to recognize Quranic reciters, it is imperative to incorporate some key factors. These key factors start with the utilization of high- quality datasets for both training and assessing recognition models. The datasets should encompass several different reciters, styles, and accents, constructing such datasets and making them available to the research. community is perhaps the most important priority in this field. Furthermore, feature extraction methods are a vital key within the entire recognition system. Many researchers employ MFCC in their studies due to the high efficacy of this technique in capturing the spectral characteristics of audio signals, however, there is a need to conduct experimental studies to investigate and compare the different methods and introduce a reliable method with the ability to capture the unique characteristics of Quranic recitation, such as pitch, intonation, and rhythm. Regarding the classification techniques, there are a wide range of algorithms/techniques are utilized. The efficacy of deep learning, specifically CNNs, RNNs, and LSTM in voice recognition has been substantial. However, there is a need to an algorithm that is tailored to address the unique difficulties encountered in Quranic recitation, such as the diverse range of styles and intonations. Finally, conducting several experimental studies using all previous factors would result with introducing a robust tailored framework for Quran reciters recognition.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ibrahim Ahmed Alomari	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Asma Al-Shargabi		✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	
Mohammed Hadwan	✓								✓			✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this work.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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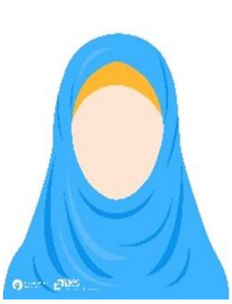
BIOGRAPHIES OF AUTHORS

Ibrahim Ahmed Al-Omari received the B.Sc. degree in information technology from Qassim University, Saudi Arabia, in January 2020. He is currently a student of the M.Sc. degree in information technology in Qassim University, Saudi Arabia. His research interests include IoT and machine learning. He can be contacted at email: ibrahim1417s@gmail.com.



Asma Al-Shargabi received her Ph.D. from De Montfort University, UK at 2015. She received her B.Sc. and M.Sc. in computer science from UST, Yemen in 1999 and 2006 respectively. She is an assistant professor at Department of Information Technology, Qassim University, Saudi Arabia from 1-12-2019 to current. She worked at University of Science and Technology (UST), Sana'a, Yemen from 1-6-2015 to 30-10-2019. Her research interests include AI, data science, IoT, Arabic language processing, cybersecurity, ubiquitous computing, and software engineering. She can be contacted at email: as.alshargabi@qu.edu.sa.

Mohammed Hadwan received the B.Sc. degree in computer science from National University, Taiz, Yemen, in 2003, the M.Sc. degree in computer science from the School of Computer Sciences, University Science Malaysia (USM), Penang, Malaysia, in 2006, and the Ph.D. degree in computer science (artificial intelligence) from the Faculty of Information Science and Technology, National University of Malaysia (UKM), in 2012. From March 2012 to December 2015, he was the Dean of the Engineering and Information Technology College, Al Saeed University, Taiz. From May 2014 to March 2016, He was the Head of the Department of Computer Science, Faculty of Applied Sciences, Taiz University. He was a staff member with the Department of Information Technology, College of Computer, Qassim University. He is also the head of the accreditation committee and the program manager of the B.Sc. degree with the Department of Information Technology. His research interests include AI algorithms and applications in general, optimization, big data, the internet of things, speech recognition, e-business, and e-commerce. He is also a member of the Data Mining and Optimization (DMO) Group and the Intelligent and Analytics Group (IAG). He is also an active researcher and a reviewer of several international and local journals. He is a member of IEEE. He can be contacted at email: dr.hadwan@yahoo.com.