Using Deep Learning for Automatically Determining Correct Application of Basic Quranic Recitation Rules

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Abstract: *Quranic Recitation Rules (Ahkam Al-Tajweed) are the articulation rules that should be applied properly when reciting the Holy Quran. Most of the current automatic Quran recitation systems focus on the basic aspects of recitation, which are concerned with the correct pronunciation of words and neglect the other Ahkam Al-Tajweed that are related to the rhythmic and melodious way of recitation such as where to stop and how to "stretch" or "merge" certain letters. The only existing works on the latter parts are limited in terms of the rules they consider or the parts of Quran they cover. This paper comes to fill these gaps. It addresses the problem of identifying the correct usage of Ahkam Al-Tajweed in the entire Quran. Specifically, we focus on eight Ahkam Al-Tajweed faced by early learners of recitation. In the first part of our work, we used traditional audio processing techniques for feature extraction (such as Linear predictive Code (LPC), Mel-Frequency Cepstral Coefficient (MFCC), Wavelet Packet Decomposition (WPD) and Markov Model based Spectral Peak Location (HMM-SPL)) and classification (such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest (RF)) on an in-house dataset of thousands of audio recordings covering all occurrences of the rules under consideration in the entire Holy Quran by different reciters of both genders. In this part, we show how to improve the classification accuracy to surpass 97.7% by incorporating deep learning techniques. Specifically, this result is obtained by incorporating most traditional features with ones extracted using Convolutional Deep Belief Network (CDBN) while the classification is performed using SVM.*

Keywords: *Articulation rules (Ahkam Al-Tajweed), Mel-Frequency Cepstral Coefficient (MFCC), Linear predictive Code (LPC), Wavelet Packet Decomposition (WPD), Hidden Markov Model based Spectral Peak Location (HMM-SPL), Convolutional Deep Belief Network (CDBN); k-Nearest Neighbors (KNN); Support Vector Machines (SVM); Artificial Neural Network (NN), Random Forest (RF), multiclass classifier, bagging; t-Test.*

Received February 14, 2018; accepted April 13, 2018

1. Introduction

The Holy Quran is the main sacred book of Islam. It is composed of 30 chapters. The verses of the Quran are 6,236 verses grouped into 114 groups called "Surahs". Correct pronunciation of Quran verses during recitation is called in Arabic "Tajweed." Rules for recitation (Ahkam Al-Tajweed) must be considered in order to ensure the delivery of the correct meaning of these verses. There are many things that should be considered for perfect recitation including knowing the principles of Arabic pronunciation in a melodious voice.

There are many issues in teaching Ahkam Al-Tajweed. One of the major problems is that, to perfectly learn Ahkam Al-Tajweed, an expert is required, and a special kind of private tutoring needs to be practiced, which is called "Talqeen." Such requirements are not always available. To tackle this issue, some researchers, turned to Machine Learning (ML) techniques to develop computerized systems to check the proper application of Ahkam Al-Tajweed based on the audio recordings of the user. However, the existing systems are limited in the rules they consider, or the Quran verses they cover. In this paper, we address this problem and build a highly accurate and efficient system that considers all Ahkam Al-Tajweed faced by early learners in the entire Holy Quran.This work consists of many steps. First, we consult with experts on teaching Quran recitation about the rules to take into consideration and the common mistakes made by the students in their early stages. Accordingly, we collect audio recordings of all verses in the Holy Quran that contain these rules. The second step is to apply traditional and non-traditional feature extraction techniques that are commonly used in the speech processing community. After extracting the features of each recording, we experiment with different classification techniques commonly used for audio classification. We also perform several tests to determine the significance of the extracted features. The goal is to extract as few features as possible without affecting the accuracy of the system. Our final model has an accuracy exceeding 97.7%.

This paper is structured as follows. Related work is briefly discussed in section 2. Then, the proposed method and the experiments conducted to evaluate it are explained in sections 3 and 4, respectively. Finally, a conclusion of the paper along with future directions is given in section 5.

2. Related Works

For several years, great efforts have been devoted to the study of Arabic speech by many researchers. There already exist detailed reviews of the evolution of Arabic using Automatic Speech Recognition (ASR). In this section, only works related to Holy Quran are highlighted.

The authors of [24] created a system based on ASR techniques to help non-native Arabic speakers learn the correct recitation of some Quran verses. This offline system works in several steps. At each step, the system processes each word separately and saves it into a codebook. The codebook data is then compared with the database of correct recitations. If there is a wrong recitation, the system indicates this to the user and displays the correct recitation. This system gives an excellent accuracy of about 92%. However, it only considers a small number of Quran verses.

A Computer Aided Pronunciation Learning (CAPL) system called HAFSS was developed by [21] based on ASR techniques. The system was built to help individuals learn the correct pronunciation of Quran verses. To achieve this, Maximum Likelihood Linear Regression (MLLR) was used in speaker adaptation block diagram, which used acoustic models and compared them to acoustic properties in order to boost system performance. To account for human errors and variance, HAFSS was represented in the form of a linear lattice that is flexible enough to support error hypothesis addition, deletion and overlapping of probable mispronunciation. HAFSS is based on the tri-phone state Hidden Markov Model (HMM), where each state is modelled after a mix of Gaussians.

The database used by this system consists of 507 utterances tested and evaluated by language experts and labeled with actual pronounced phonemes that are used to compare and evaluate the recognized speech. The system achieved 97.87% accuracy surpassing a message-based system performance which only achieved 80.13% accuracy. An enhancement on this system based on Speaker Adaptive Training (SAT) was discussed in [1] to address the problem of user enrolment time associated with ASR systems. The authors measured the correlation between the judgments of human experts and HAFSS system. They also measured the proficiencies of beginner users before and after using the system.

A Quran recognizer is described in [8]. The system considers the 30th chapter of the Quran which includes over 2,000 distinct words. Based on MLLR, a speaker independent speech recognition system was then developed. This process allows for the adaptation of recognizing speech without cues of a specific speaker. This is accomplished through global Regression Class Tree (RCT) and MLLR adaptation. The system displayed an obstacle in terms of recognition time due to the large number of states of its HMM. The level of accuracy of the system was in the range 68-85%.

Perhaps, the closest to our work is the work conducted at the J-QAF laboratories, which sought to improve the teaching of the Holy Quran. These laboratories use the traditional methods for teaching the Quran, where the students learn directly from an expert in Quran recitation. A study [11] was conducted on how this method can become electronic without the need for the presence of expert teacher. Literature related to this work state that Mel-Frequency Cepstral Coefficients (MFCC) features give the best accuracy in analysing the verses. This study led to the development of a system that corrects the recitation for the user in two small Surahs: “AlFatiha” and “AlEkhlas”, by extracting the features from different recitations and different expert readers for previous small chapters of Quran, then using HMM to map each feature to related text [13]. Multiple recitations from multiple readers are used for reference, raising the accuracy for correct recitation to 98%. Here, the authors only consider four recitation rules in a very small part of the Quran. In our work, we consider the correct as well as incorrect application of eight recitation rules in the entire Holy Quran.

We notice that existing systems on the classification and correction for Ahkam Al-Tajweed are limited in their coverage of the Holy Quran [8, 12, 22] and the recitation rules (the number of rules do not exceed four rules for each system [1, 12, 13, 21]). Also, they assume that the verse being recited is known [13]. Finally, there have been very limited efforts invested in using deep learning approaches for Arabic speech processing with almost no special attention to Quranic recitation [3]. Our work comes to fill these gaps.

3. Proposed Approach

Our goal is to build a system capable of determining which one of the Ahkam Al-Tajweed is used in a specific audio recording of a Quranic recitation. The Ahkam Al-Tajweed we consider are eight: “EdgamMeem” (one rule), “EkhfaaMeem” (one rule), “Ahkam Lam” in ‘Allah’ Term (two rules) and “Edgam Noon” (four rules). Moreover, we consider both correct and incorrect usage of each rule. Hence, our classification problem involves 16 classes. Finally, unlike previous works, ours covers the entire Holy Quran. We start our discussion of our approach with the dataset description. Then, we discuss the feature extraction and classification steps using popular techniques from the speech processing literature.

3.1. Dataset

Our dataset consists of 3,071 audio files, each containing a recording of exactly one of the eight rules under consideration (in either the correct or the incorrect usage of the rule). We collect these recordings from ten different expert reciters (five males and five females). Table 1 shows the number of audio recordings for each rule and how they are distributed across the two genders. After their collection, the recordings are pre-processed and the part that contains the rule is extracted.

3.2. Feature Extraction Techniques

In this work, we employ two types of feature extraction techniques: traditional and non-traditional. For the traditional type, four feature extraction techniques are used. As for the non-traditional type, Convolutional Deep Belief Network (CDBN) is used. We cover these techniques in the following subsections:

Table 1. The number of audio recordings for each rule (showing both the correct and incorrect usage of this rule).

Rule	Correct?	Recordings by males	Recordings by females
R1: EdgamMeem	Correct	60	60
	Incorrect	30	-
R2: EkhfaaMeem	Correct	60	60
	Incorrect	30	-
R3: Tafkheem Lam	Correct	88	512
	Incorrect	55	407
R4: Tarqeeq Lam	Correct	60	195
	Incorrect	30	134
R5: Edgam Noon (Noon)	Correct	138	138
	Incorrect	-	68
R6: Edgam Noon (Meem)	Correct	107	106
	Incorrect	-	53
R7: Edgam Noon (Waw)	Correct	52	52
	Incorrect	-	26
R8: Edgam Noon (Ya')	Correct	221	219
	Incorrect	-	110

3.2.1. Traditional Techniques for Features Extraction

several processing techniques are discussed in the literature for extracting the features from auditory data. We select the popular feature extraction techniques such as Linear Predictive Code (LPC), Mel-frequency Cepstral Coefficients (MFCC) and Multi-Signal Wavelet Packet Decomposition (WPD) in addition to less popular techniques such as Hidden Markov Model based Spectral Peak Location (HMM-SPL). Details of what these techniques are and how we employ them are given in an earlier publication of this work [7].

3.2.2. Non-Traditional Techniques for Features Extraction

Convolutional Restricted Boltzmann Machines (CRBM) [15, 17] is the main component of CDBN. In our work, we follow the formulation of [15] for CRBM, where it was applied to auditory data. The steps are as follows. First, the time-domain signals were converted to spectrograms in order to extract the spectrogram from each audio file. Spectrogram had a 20ms window size and 10ms overlap. Second, since spectrograms have large dimensionality, Principle Component Analysis (PCA) whitening was applied with 80 components in order to create a lower dimensional representation of spectrogram. Third, the 300 first layer bases were trained with filter length equal to six and max pooling ratio (local neighborhood size) of three. Then, the second 300 layer bases were trained using the first layer activations on unlabeled dataset. Finally, the output models from training processes are used to extract out the features from the dataset for each labelled class. Then, we find the mean and SD for first and second layer features as we do in the traditional techniques.

3.3. Classification

Several classifiers are considered in our work. We give attention to the classifiers that have done well in other works related to audio classification in general and, specifically, for speech processing. Two types ofclassifiers are considered as described in the following subsections:

3.3.1. Nonlinear ML Algorithms

These types of ML algorithms use one-layer processing. They also do not have ability to find the relationship between input attribute and the output attribute being predicted. In the following, we list the most popular nonlinear classification algorithms we consider:

- *k-NearestNeighbors (KNN)*: this algorithm works by saving the entire training data, and when a prediction is requested on a certain instance, it tries to locate the k most similar instances in the training data[18,23].
- *Support Vector Machines (SVM)*: SVM works by trying to find the best line that separates the data into several groups. An optimization process is used for this purpose[9].
- *Artificial Neural Network (ANN)*: the ANN classifier we employ is called Multilayer Perceptron (MLP), in which a set of appropriate outputs are mapped from a set of input data. An MLP is a directed graph with multiple layers of nodes. All nodes in each level are fully connected with the next level. Each node is a processing element with a function. In order to train the model, a supervised learning technique called backpropagation is used. MLP is a developed version of standard linear perceptron, in which the data that are not linearly separable can be distinguished.

3.3.2. Ensemble ML Algorithms

More accurate predictions can be obtained by carefully combining the predictions from multiple models. This is done using EnsembleMLalgorithms. We list the popular Ensemble algorithms we consider:

- *Random Forest (RF)*: RF is a strong classifier used in ML field. This classifier has several strong points such as its high classification accuracy, its non-parametric nature and its ability to determine the importance of variables. RF classifier is considered to be a part of the black box type because the classification split rules are unknown[20].
- *Multiclass Classifier*: it is a meta classifier used to link multiclass datasets with second class classifier. It can also increase the accuracy by applying error correcting output codes. This classifier has a base classifier that can be selected manually. In our work, the base classifier is set to the RF classifier. This choice is made after an extensive set of experiments.
- *Bagging*: in order to improve classifier stability, accuracy and reduce variance, bootstrap aggregating approach is used. It works as follow. It uses sampling with replacement to create replicates of the dataset, and, then, for each replica, it builds a model. Then, all created models are used in a classifiers ensemble. A single outcome will be computed by combining individual outcomes [6].

4. Experiments and Results

In this section, we discuss the experiments we conduct and analyze the obtained results. The parts related to the evaluation of traditional feature extraction techniques were reported in [7]. In this work, we show the results of applying deep learning approach for featuresextracting. Finally, a summary of the results and the results of testing our model on new verses are discussed.

Before going into the experiments, let us discuss the experimental setup we use.We use the Weka tool [25] for testing and classification purposes. The testing technique we follow is the 10-fold cross-validation. As for accuracy measures, we report the most popular measures used in the literature. Particularly, for every single classifier, the weighted Precision/Recall values, F-score (F1), Accuracy and ROC are reported, where ROC represents the area under the Receiver Operating Characteristic (ROC) curve [4, 16]. We also report the time needed to build each model.

In our experiments, the features are computed using CDBN. Similar to what the authors of [15] did, Table 2 shows the results of using CDBN to extract layer one (L1) features, layer two (L2) features, in addition to the combination of the features of the two layers. The table also shows the results of combining CDBN features (L1 and L2) with the best settings from the previous experiments: all traditional features, best features after feature type's ablations and best features after applying feature selection. The best results are when we are applying SVM classifier to CDBN features with (MFCC, WPD and mean of HMM-SPL features).We notice that best accuracy for classification process can be obtained using features for two CDBN layers with the results of feature ablation process.As in [15], our work proves that CDBN can get more accurate results, since good classifications results depend on the well-engineered features. Also, we can notice that using feature selection gives the same results as using the smallest set of features after ablation.

Table 2. Experiments results using CDBN features.

Features	Precision	Recall	F-measure	ROC Area	Build Time	Accuracy
CDBN L1	0.971	0.970	0.970	0.996	3.630	0.970
CDBN L2	0.971	0.971	0.971	0.996	2.480	0.971
CDBN L1 + CDBN L2	0.977	0.977	0.977	0.997	4.500	0.977
CDBN + Feature Ablation Results	0.978	0.978	0.977	0.997	5.330	0.978
CDBN + Feature Selection Results	0.978	0.978	0.978	0.997	5.330	0.978
Traditional features	0.942	0.941	0.941	0.993	4.300	0.941

After conducting all of our experiments, we conclude that we can build our model using small set of traditional features combined with CDBN features. Table 3 shows a summary of these features. Note that the time needed for extracting these 1814 features is 15.2 seconds for each audio file. Existing systems discussed in the literature depend on prior knowledge of the Quranic verse being recited [13] and only cover small chapters of the Quran [2, 5, 8, 10, 12, 14, 19, 22]. Such systems do not support the ability to determine the recitation rule in a new verse. Our system comes to fill this gap. We test our system with verses that are excluded from the training process.

In these experiments, we use the features that are found to be most useful by the experiments in the previous sections (viz., MFCC features, WPD features, mean of HMM-SPL features and features using CDBN). Table 4 lists the results of applying our system on a subset of our dataset consisting of the recordings of two reciters. The dataset is separated into:

1. A training part consisting of 70% of the samples (1214 verses) and
2. A testing data part consisting of 30% of the samples (525 verses).

Note that this dataset contains samples of 14 classes.

Table 3. Summary of Features.

Technique	# Features
MFCC	100
WPD	508
HMM-SPL	6
CDBN	1200

Table 4. Experiments Results while Testing Our Model using New Verses.

Classifier	Precision	Recall	F-Measure	ROC Area	Test Time	# instances	Accuracy
Bagging	0.958	0.956	0.956	0.996	2.840	502	0.956
RF	0.857	0.840	0.829	0.989	0.300	441	0.840
ANN	0.906	0.886	0.877	0.988	3.310	465	0.886
SVM	0.966	0.964	0.963	0.993	1.130	506	0.964

Table 4 results prove that our model can identify the recitation rule in a verse on which it is not trained with accuracy 96.4%. Also, we note that using SVM classifier gives the most accurate results (506 out of 525 instances classified correctly). As for the testing time, it is very fast as it manages to give decisions on all testing instances in a second.

5. Conclusions and Future Work

In this work, we addressed the problem of determining the recitation rule used by the user (reciter of the Holy Quran) and whether this rule is correctly used or not. We considered eight rules in both correct and incorrect forms. Thus, the decision to be made by the proposed system is one out of 16. Treating this problem as a classification problem, we collected a large dataset of audio recordings by several experts of both genders on all occurrences of the rules under consideration. We then applied several feature extraction techniques both traditional (such as MFCC, LPC, etc.,) and new (such as CDBN). We also experimented with feature ablation and feature selection. Finally, several classifiers are used such as SVM, RF, etc.

The results showed that the best results can be obtained by using MFCC, WPD, HMM-SPL and CDBN for feature extraction and SVM for classification. Our experiments showed that excluding LPC features has no effect, since LPC didnot divide the signal to specific windows and determine the overlapping between these windows-each pth-order only depend on the pth-1 only in LPC-. As part of our future plans, we aim to focus on building an end-user tool (e.g., a smart phone application) based on the best results we obtain. The goal is to have a user-friendly, efficient and accurate tool that can help early learners of Quran Recitation improve their skills.

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