Automatic Pronunciation Error Detection and Correction of the Holy Quran's Learners Using Deep Learning

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Abstract

Assessing spoken language is challenging, and quantifying pronunciation metrics for machine learning models is even harder. However, for the Holy Quran, this task is enabled by the rigorous recitation rules (tajweed) established through the efforts of Muslim scholars, making highly effective assessment possible. Despite this advantage, scarcity of high-quality annotated data remains a significant barrier. In this work, we bridge these gaps by introducing: (1) A 98% automated pipeline to produce high-quality Quranic datasets – encompassing: Collection of recitations from expert reciters, Segmentation at pause points (waqf) using our fine-tuned wav2vec2-BERT model, Transcription of segments, Transcript verification via our novel Tasmeea algorithm; (2) 848 hours of audio (286K annotated utterances); (3) **qdat_bench** benchmarks phonemes, diacritization, and Tajweed rules (Ghunnah, Qalqalah, Madd) on real recitation errors containing 159 samples; (4) A novel ASR-based approach for pronunciation error detection, utilizing our custom Quran Phonetic Script (QPS) to encode Tajweed rules (unlike the IPA standard for Modern Standard Arabic). QPS uses an 11-level script: (Phoneme level): Encodes Arabic letters with short/long vowels. (Sifat level): Encodes articulation characteristics of every phoneme. We further include comprehensive modeling with our novel multi-level CTC Model which achieved 0.21% and 1.94% average Phoneme Error Rate (PER) on the testset and qdat_bench respectively, with 75.8% Tajweed F1 score and 84.7% accuracy on the benchmark. We release all code, data, and models as open-source: https://obadx.github.io/quran-muaalem/en/

Keywords: Mispronunciation Detection Model, Arabic Natural Language Processing, End-to-end Models

1 Introduction

Assessing pronunciation is not a simple task Kheir et al., 2023, as it does not only rely on pronouncing phonemes correctly but also involves other factors like intonation, prosody, and stress. Does learning these mean one is done? No—other factors include fluency and completeness Kheir et al., 2023. However, the Holy Quran presents unique

characteristics: it is among the easiest spoken texts to learn despite containing special phonemes absent in other languages.
The pronunciation of the Holy Quran is governed by rigorously strict rules formally defined by ancient Muslim scholars since the 6th century. Despite their beauty and precision, these rules have not been comprehensively digitized (to our knowledge) for Quranic pronunciation assessment.
Although RDI pioneered computer-aided Quranic instruction Sherif et al., 2007, they neither disclosed their phoneticization process nor released data/models. Consequently, new research must start from basics: defining phoneticization, data, and models. To bridge this gap, we introduce:

- **A Phonetizer**: Encodes *all* Tajweed rules and articulation attributes (*Sifat*) defined by classical scholars, except *Ishmam* (إشمام)
- **A 98% automated pipeline**: Generates highly accurate datasets from expert recitations
- **A dataset**: ∼286K annotated utterances (848 hours)
- **qdat_bench**: Benchmarks phonemes, diacritization, and Tajweed rules (Ghunnah, Qalqalah, Madd) on real recitation errors containing 159 samples
- **Integration**: Our multi-level CTC model proves the Quranic phonetic script is learnable (0.21% average phoneme error rate)

The paper is organized as follows:

- **Related Work**: Expands on strengths/weaknesses of prior research
- **Quran Phonetic Script**: Introduces our two-level script: **phonemes** and **Sifat** (10 attributes → 11 total levels)
- **Data Pipeline**: Stages include:
  1. Digitized Quran script as foundation
  2. *Hafs* methodology criteria
  3. Expert recitation collection
  4. Segmentation at pause points (وقف)
  5. Segment transcription
  6. Validation via *Tasmee* (تسميع) algorithm
- **Modeling**: Demonstrates learnability of the phonetic script
- **Results**: Analysis of outcomes
- **Limitations & Future Work**: Next research directions
- **Conclusion**: Summary of contributions
- **Appendix**: Details on *Mushaf* attributes and algorithms

2 Related Work

2.1 Quran Pronunciation Datasets

We discuss the most important datasets here. everyayah[1] is the largest openly available dataset with 26 complete *Mushafs* segmented and annotated by Ayah by experts like Al Hossary and non-experts such as Fares Abbad. Qdat Osman et al., 2021 contains 1509 utterances of single specific Ayahs labeled for three rules: Madd, Ghunna, and Ikhfaa. Although the scale is relatively small, it was widely adopted by the community Omran et al., 2023a, and Shaiakhmetov et al., 2025 due to being open-source. The Tarteel v1 dataset Khan et al., 2021 consists of 25K utterances with diacritics and no Tajweed rules. The latter is the Tarteel[2] private dataset, a massive 9K-hour collection annotated with diacritics without Tajweed rules. The most recent benchmark is IqraaEval Kheir et al., 2025, which presents a test set of 2.2 hours from 18 speakers, but uses Modern Standard Arabic (MSA) without Tajweed rules.

2.2 Quran Pronunciation Models

To our knowledge, the first work addressing automated pronunciation assessment for the Holy Quran is RDI Sherif et al., 2007, which built a complete system for detecting pronunciation errors. The work does not specify which errors were included or excluded but mentions testing Qalqala, Idgham, and Iqlab rules. It also omits details on Quranic word phoneticization. Subsequent work continued with Abdou and Rashwan, 2014 and Al-Marri et al., 2018, using Deep Neural Networks (DNNs) to replace HMMs and improve the system. Many studies rely on modeling phoneme duration for duration-dependent rules like Madd and Ghunna, e.g., Mohammed et al., 2017, Alqadasi et al., 2023, but use limited datasets and focus on specific verses rather than the entire Quran. Others concentrate on detecting specific rules like Qalqala Omran et al., 2023a or Ghunna and Madd Shaiakhmetov et al., 2025, Alsahafi and Asad, 2024. However, most efforts except RDI work train on small-scale datasets from specific Quranic chapters.
At this point, Tarteel emerges; though lacking Tajweed rules, they built a robust ASR system for diacritized character detection. They developed a crowd-sourced dataset Khan et al., 2021 of 25K utterances (68 hours), later extended via application users to 9K hours of private annotated data. The work most aligned with our vision of detecting all error types (including Tajweed and *Sifat*/articulation attributes) is Putra et al., 2012. Although it relies on HMMs and minimal data, it introduces a multi-level detection system: *Makhraj* (phoneme level) and Tajweed rules level.

2.3 Pretrained Speech Encoders with Self-Supervised Learning (SSL)

Speech pretraining began early Hinton and Salakhutdinov, 2006 but was constrained by the sequential nature of Recurrent Neural Networks (RNNs) Hopfield, 1982. The rise of Transformers Vaswani et al., 2017 facilitated greater GPU parallelization, enabling large-scale pretraining. BERT Devlin et al., 2019 using Masked Language Modeling (MLM) introuduce large unsuprvised pretraing which has better results on down

[1] everyayah.com
[2] tarteel.ai

stream taks. This soon extended to speech with wav2vec Schneider et al., 2019 and wav2vec2.0, which added product quantization Baevski et al., 2020. Conformer later replaced vanilla Transformers for speech by integrating convolution Gulati et al., 2020. Google's Wav2Vec2-BERT Chung et al., 2021 then applied MLM to speech. Finally, Facebook extended Wav2Vec2-BERT pretraining Barrault et al., 2023 to 4.5M hours (including 110K Arabic hours), ideal for low-resource language fine-tuning.

3 Quran Phonetic Script

We consider the Quran Phonetic Script to be the most valuable and important contribution of our work. By formalizing the assessment of Holy Quran pronunciation as an ASR problem represented through this script, we provide a comprehensive solution to the task.
Modern Standard Arabic (MSA) orthography cannot adequately represent Tajweed rules for error detection. For example, MSA cannot measure the precise length of Madd rules. Previous research (e.g., Omran et al., 2023b) focused on single rules like Qalqalah. Our phonetic script addresses this limitation by capturing all Tajweed pronunciation errors except Ishmam (إشمام), which involves a visual mouth movement without audible output. We based our script on classical Muslim scholarship rather than the International Phonetic Alphabet (IPA) for these reasons:

1. **Historical Precedence**: Muslim scholars from the 6th to 14th centuries rigorously defined Quranic errors centuries before modern phonetics emerged in the West.

2. **Scientific Foundation**: Scholars like Al-Khalil ibn Ahmad (6th century AH) systematically described articulations and attributes with remarkable accuracy comparable to modern phonetics هبيرة, عز, 2023.

3. **Pedagogical Relevance**: Learners' errors align with classical definitions according to expert Quran teachers.

Following أمين رشدس سويد, 2021, Quran recitation errors fall into three categories:

- **Articulation Errors**: Incorrect pronunciation of phonemes

- **Attribute Errors**: Mistakes in letter characteristics (Sifat al-Huruf)

- **Tajweed Rule Errors**: Incorrect application of rules like Ghunnah, Madd, etc.

Our script comprehensively addresses all three aspects through main two output levels:

- **Phonemes Level**: Represents letters, vowels, and Tajweed rules

- **Sifat Level**: Consists of 10 levels representing articulation attributes for each phoneme

Refer to tables: 7 8 for Phonemes and Sifat levels.
Our script has some important charactirstics:

- Normal Madd appears as consecutive madd symbols (e.g., 4-beat Madd: اااا)

- Madd al-Leen represented with multiple waw/yaa symbols
- Stressed Ghunnah (e.g., النون المشددة) as three consecutive noon symbols (ننن)
- Ikhfa represented as three consecutive noon_mokhfah (ں) or meem_mokhfah (ࢲࢲࢲ)
- Assimilation represented by doubling (e.g., مَن يَعْمَلْ → مَييَعمَل)
- Sakin: No following symbol
- Imala: fatha_momala and alif_momala
- Rawm: dama_mokhtalasa marker

Example: In table 1 shows how our phonetizer works. This example showes the phonetization of word (أَتُحَٰٓجُّوٓنِّى) as a row by row: The firt row showes conversion of (أَ) to (ءَ) with its sifat in the row. following the second row. For the forth row showing the madd lazem rule with 6 beats phonetized as 6 alifs (اااااا) same as the sixth row but with damma represented as 6 waw_madd (ۥۥۥۥۥۥ) And for the fifth row we notice that we converted (جُّ) to (ججُ) as we dissmple shadda. The last row showes the normal madd of yaa with two beats represented as two yadd_madd (ۦۦ).

Table 1: Examples of Uthmani to Phonetic Script Conversion with Sifat Attributes. This example showes the phonetization of word (أَتُحَٰٓجُّوٓنِّى) as a row by row: The firt row showes conversion of (أَ) to (ءَ) with its sifat in the row. following the second row. For the forth row showing the madd lazem rule with 6 beats phonetized as 6 alifs (اااااا) same as the sixth row but with damma represented as 6 waw_madd (ۥۥۥۥۥۥ) And for the fifth row we notice that we converted (جُّ) to (ججُ) as we dissmple shadda. The last row showes the normal madd of yaa with two beats represented as two yadd_madd (ۦۦ)

Uthmani	Phonetic	H/J	S/R	T/T	Itb	Saf	Qal	Tik	Taf	Ist	Gho
أَ	ءَ	jahr	shd	mrq	mnf	no	nql	nkr	ntf	nst	nmg
تُ	تُ	hams	shd	mrq	mnf	no	nql	nkr	ntf	nst	nmg
حَ	حَ	hams	rkh	mrq	mnf	no	nql	nkr	ntf	nst	nmg
ـَٰٓ	اااااا	hams	rkh	mrq	mnf	no	nql	nkr	ntf	nst	nmg
جُّ	ججُ	jahr	shd	mrq	mnf	no	nql	nkr	ntf	nst	nmg
وٓ	ۥۥۥۥۥۥ	jahr	rkh	mrq	mnf	no	nql	nkr	ntf	nst	nmg
نِّ	ننِن	jahr	btw	mrq	mnf	no	nql	nkr	ntf	nst	mg
ى	ۦۦ	jahr	rkh	mrq	mnf	no	nql	nkr	ntf	nst	nmg

Attribute Abbreviations:
H/J: Hams/Jahr S/R: Shidda/Rakhawa T/T: Tafkheem/Taqeeq Itb: Itbaq
Saf: Safeer Qal: Qalqla Tik: Tikraar Taf: Tafashie Ist: Istitala Gho: Ghonna
Value Abbreviations:
shd: shadeed rkh: rikhw btw: between mrq: moraqaq
mof: mofakham mnf: monfateh mtb: motbaq no: no_safeer
nql: not_moqalqal nkr: not_mokarar ntf: not_motafashie
nst: not_mostateel nmg: not_maghnoon mg: maghnoon

3.1 Development Methodology

Our phonetization has two steps:

1. **Imlaey to Uthmani Conversion**
   We selected Uthmani script as our foundation because:
   - Contains specialized Tajweed diacritics (Madd, Tasheel, etc.)
   - Preserves pause rules critical for recitation (e.g., stopping on رحمت)

   In order to do that, we created an annotation UI to manually annotate misaligned words in both scripts. For example 2, after that, we developed an algorithm that relies on the annotations to convert Imlaey to Uthmani.

2. **Uthmani to Phonetic Script Conversion**
   We implemented the process through 26 sequential operations. Each operation contains one or more regular expressions, as shown in the Appendix 8.2.

3. **Extracting Sifat**: Next, we extract the 10 attributes (Sifat) defined in Table 8, excluding **Inhiraf** (إنحراف), as it describes the shidda/rakhawa spectrum, and **Leen** (اللين), as it was already handled through our Madd representation.

Table 2: Example of misalignment between Uthmani and Imlaey Scripts

Imlaey Script	Uthmani Script
يَا ابْنَ أُمَّ	يَٰبْنَؤُمَّ

4 Data Preparation

To prepare the data, we first defined selection criteria. We aimed to collect recitations from the best reciters worldwide to serve as references for judging Quran learners. In our study, we considered only *Hafs* riwayah (رواية حفص) as it's the most popular recitation method globally. Recognizing that manual data annotation requires significant effort and time, we created a 98% automated pipeline for data collection. The steps are: (1) Choose a digitized Quran script as the project foundation. (2) Define criteria for *Hafs* methodology. (3) Collect expert recitations (4) Segment recitations at pause points (وقف) (5) Transcribe segments. (6) Validate data through *Tasmee* (تسميع) Algorithm. (7) Develop Quran Phonetic Script.
We define a *Moshaf* as a complete Quran recitation (chapters 1-114) by a specific reciter. Statistics are summarized in table 3. We manually annotated 5400 samples out of 286,537 utterances, resulting for the automation ratio of 98%.

4.1 Choose a Digitized Version of the Holy Quran

The Quran has multiple digitized versions including Tanzil[3] and King Fahd Complex[4]. We chose Tanzil because:

[3] https://tanzil.net

[4] https://qurancomplex.gov.sa

Table 3: Dataset Statistics per Moshaf

Moshaf ID	**Hours**	**Length**
0.0	28.48	9133
0.1	40.31	10764
0.2	49.47	9971
0.3	37.19	12604
1.0	28.41	10939
2.0	51.05	9942
2.1	30.03	10394
3.0	25.19	10444
4.0	29.12	10994
5.0	28.02	11482
6.0	39.39	12435
7.0	28.26	9907
8.0	30.86	10330
9.0	27.95	10642
11.0	24.01	10363
12.0	33.42	9880
13.0	33.99	9377
19.0	30.11	11278
22.0	28.11	10332
24.0	28.51	9868
25.0	16.93	7922
26.0	30.44	11565
26.1	32.71	11850
27.0	28.05	11213
28.0	31.05	10535
29.0	27.79	11061
30.0	29.14	11312
Total	**847.9944402**	**286537**

- It uses standard Unicode characters
- Contains both *Imlaei* and *Uthmani* versions
- Maintains high accuracy

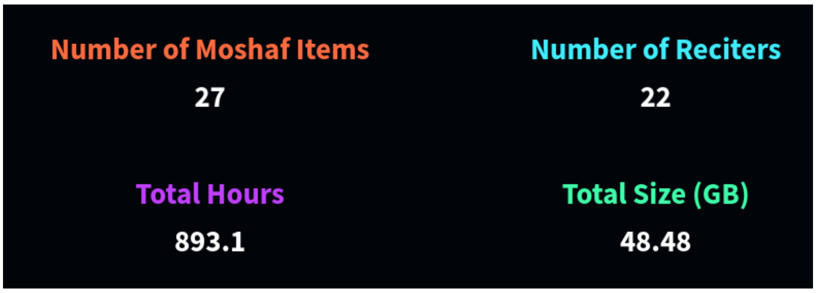
We excluded KFGQPC due to its evolving/unstable nature compared to Tanzil.

4.2 Define Variant Criteria for Hafs

Hafs riwayah contains variants, e.g., *Madd Al-Munfasil* (مد المنفصل) can extend 2, 4, 5, or 6 beats. We rigorously defined these variants through the Qira'at literature علي الضباع, 1380هـ, summarized in the following attributes in the Appendix section 8.4.

4.3 Collect Expert Recitations

We collected recitations from 22 world-class reciters with premium audio quality, totaling **893 hours** pre-filtering.



Number of Moshaf Items	Number of Reciters
27	22
Total Hours	**Total Size (GB)**
893.1	48.48

Figure 1: Database Collection Statistics

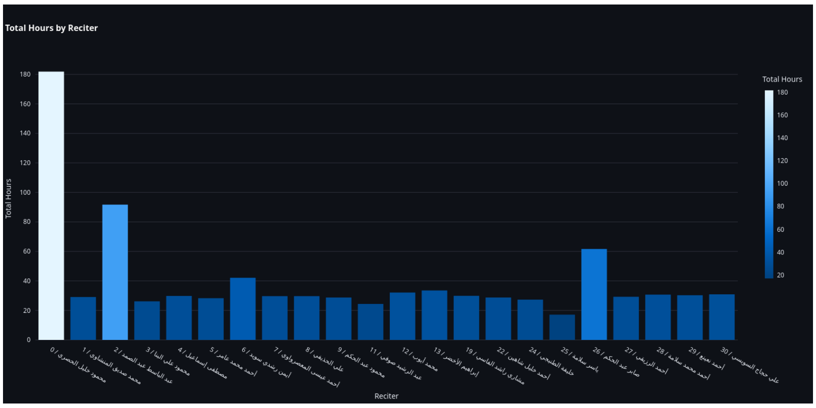


Figure 2: Reciters Statistics

We developed a web GUI using Streamlit[5] that:

- Downloads and extracts metadata for each track

[5] https://streamlit.io/

- Organizes data by Moshaf (each chapter as ”001.mp3”)
- Annotates Moshaf attributes

4.4 Segment Recitations

Since Tajweed rules are affected by pauses (وقف), accurate segmentation is crucial. We initially tested open-source Voice Activity Detection (VAD) models including SileroVAD Team, 2024 and PyAnnotate Plaquet and Bredin, 2023. Poor Quran-specific performance led us to develop a custom segmenter by fine-tuning Wav2Vec2-BERT Barrault et al., 2023 for frame-level classification.

4.4.1 Preparing Segmenter Data

We selected mosahf compatible with SileroVAD v4, using EveryAyah[6] (pre-segmented by ayah) as ground truth. After tuning parameters per Moshaf:

- Threshold
- Minimum silence duration (merges segments)
- Minimum speech duration (discards short segments)
- Padding (added at segment boundaries)

4.4.1.1 Data Augmentation Using the Audiomentations Jordal and Contributors, 2025 library, we replicated SileroVAD’s noise setup on 40% of samples, adding:

- `TimeStretch` (0.8x-1.5x) to simulate recitation speeds
- Sliding window truncation (1-second windows) for long samples instead of exclusion

4.4.2 Training Segmenter

We fine-tuned Wav2Vec2-BERT for frame classification (1 epoch):
Results of our segmenter on unseen mosahf in table 4.4.2:

Table 4: Test results of the segmenter on unseen full moshaf. The result is validated by actual usage of the segmenter

Metric	**Value**
Test Loss	0.0277
Test Accuracy	0.9935
Test F1 Score	0.99476

[6] https://everyayah.com/

4.5 Transcribe Segmented Parts

We employed Tarteel ASR AI, 2023 (Whisper fine-tuned on Quranic recitations Radford et al., 2023). To handle its 30-second limit, we used sliding window truncation (10-second windows), with verification in the next step.

4.6 Verification of Segmentation and Transcription

Segmentation Verification: Manual inspection of 50-75 random samples per Moshaf. Moshaf 25.0 was excluded due to poor segmentation.
Transcription Verification: *Tasmeea*-inspired algorithm: (1) Match segments to Quranic text. (2) Identify missing surah parts. (3) Manual correction.
Refer to the Tasmeea Algorithm in the Appendix 1
After matching, we catalogued missing Quranic portions per surah. Then correct transcription errors identified through the above process.

5 Modeling The Quran Phonetic Script

Our Quran Phonetic script has two outputs: `phonemes` and `sifat` (which has 10 attributes). We modeled this as follows: Imagine you are given an input speech utterance and want to output transcripts in Arabic, English, French, and German simultaneously. We implemented this as a speech encoder with a linear layer for each language. Replacing languages with our 11 levels (`phonemes` and the 10 sifat), we obtain 11 parallel transcription levels. We chose CTC loss Graves et al., 2006 without language model integration because we aim to capture what the user actually said, not what they intended to say. We name our architecture **Multi-level CTC**.
The final loss is a weighted average of the CTC losses from all 11 hierarchical levels. The weights are assigned based on the vocabulary size of each level to balance their contribution. Specifically, the `phonemes` level (vocabulary size 44, including blank token) receives a weight of 0.4; the `shidda_or_rakhawa` and `tafkheem_or_taqeeq` levels (each with a vocabulary size of 4 including blank token) receive a weight of 0.0605

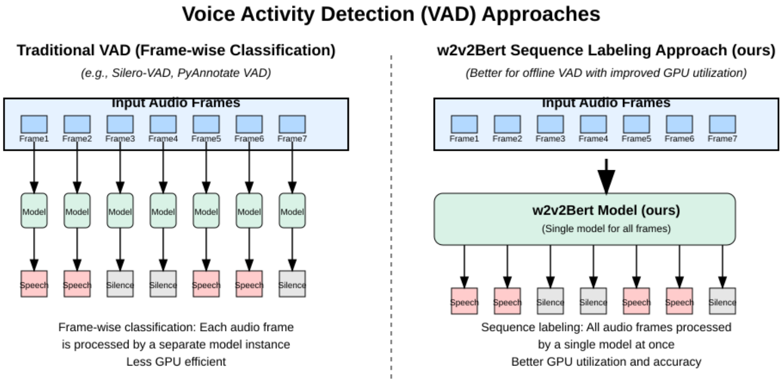

Voice Activity Detection (VAD) Approaches
Traditional VAD (Frame-wise Classification)
(e.g., Silero-VAD, PyAnnotate VAD)
Input Audio Frames
Frame1
Frame2
Frame3
Frame4
Frame5
Frame6
Frame7
Model
Speech
Silence
Frame-wise classification: Each audio frame is processed by a separate model instance
Less GPU efficient
w2v2Bert Sequence Labeling Approach (ours)
(Better for offline VAD with improved GPU utilization)
Input Audio Frames
w2v2Bert Model (ours)
(Single model for all frames)
Speech
Silence
Sequence labeling: All audio frames processed by a single model at once
Better GPU utilization and accuracy

Figure 3: VAD architecture vs. standard streaming models

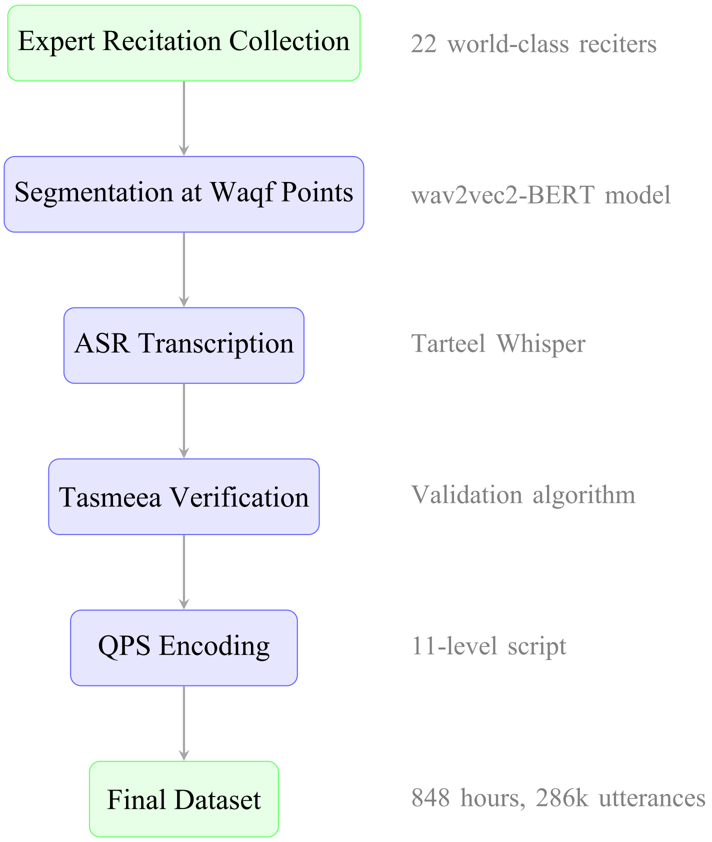


Figure 4: The complete data preparation pipeline showing the six main stages from expert recitation collection to the final dataset generation. Each stage utilizes specialized models and algorithms to ensure high-quality annotations.

each. The remaining eight levels (each with a vocabulary size of 3 including blank token) receive a weight of 0.069875 each.
`phonemes` level as it has the largest vocabulary size (43) compared to other levels.

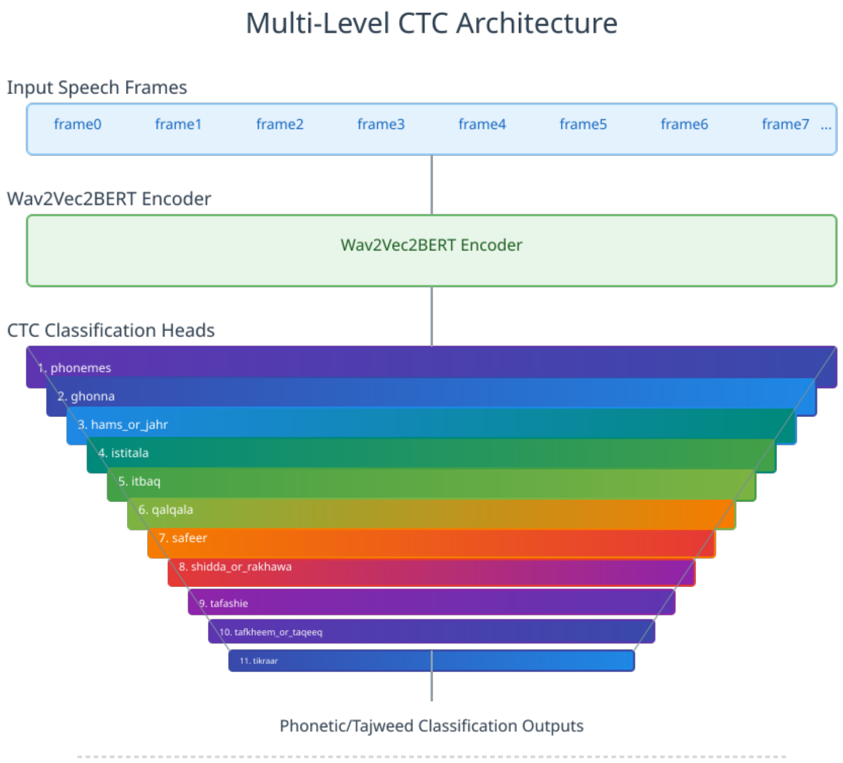


Figure 5: Multi-level CTC loss Architecture composed of 11 Heads for every level and CTC loss for every level with weighted average loss

We fine-tuned Facebook's Wav2Vec2-Bert Barrault et al., 2023 for a single epoch with a constant learning rate of `5e-5` with 64 batch size. We applied augmentations identical to Silero VAD Team, 2024 using the `audiomentations` library Jordal and Contributors, 2025, with additional augmentations: `TimeStretch` and `GainTransition`. We filtered out samples longer than `30 seconds` not due to model limitations, but for efficient GPU utilization - sacrificing only 3k samples out of 250k training samples.
The training was done using an H200 GPU with 141 GB of GPU memory for 7 hours.

6 Results

We trained on all available Mushaf datasets, reserving three Mushaf (19.0, 29.0, 30.0) for comprehensive testing. These test datasets feature expert male reciters with extensive training in Tajweed rules. The expert nature of these recordings provides an ideal evaluation environment for assessing the model's fundamental phonetic transcription

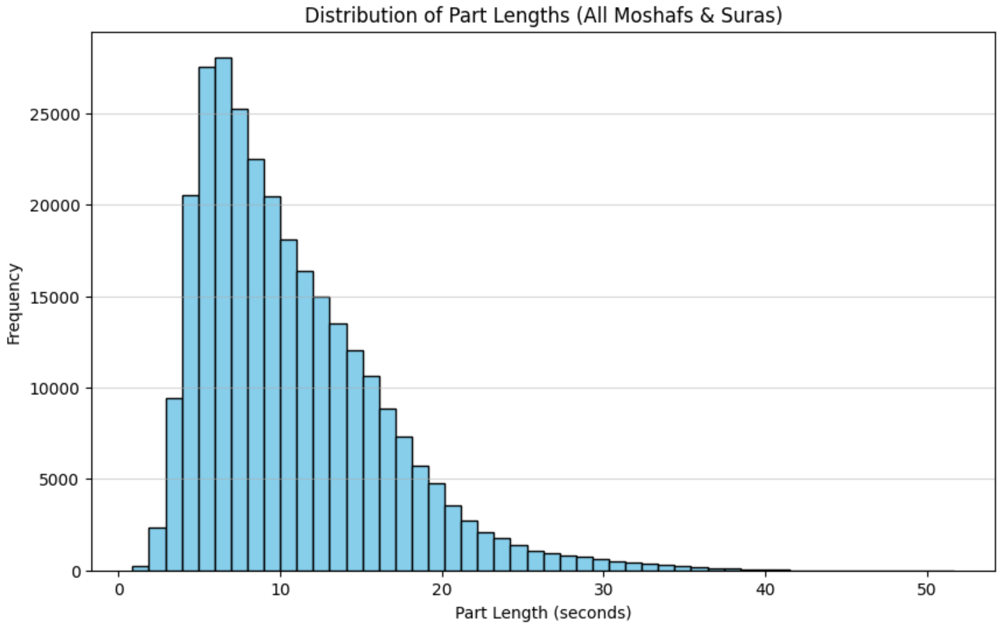


Figure 6: Recitations lengths in seconds for the whole dataset

capabilities across different representation levels. Notably, the phonemes level presents the greatest challenge with a 44-character vocabulary (including padding), resulting in the highest Phoneme Error Rate of 0.543% and average per of 0.21% across all levels as shown in Table 5, while still demonstrating excellent overall performance that validates our multi-level CTC approach.

To evaluate our model's performance on real recitation errors, we tested on our developed qdat_bench[7] benchmark, which builds upon Osman et al., 2021 after comprehensive reannotation and addition of all Tajweed rules including phonemes and 10 sifat levels. This enhanced benchmark provides F1 and MSE metrics for (F1 for: Noon Moshaddadah, Ikhfaa and Qalqlah. MSE for Madd lengths including: normal madd, separated madd and aared madd), enabling researchers to compare different representations of Tajweed rules. The results, shown in Table 6, demonstrate that despite being trained exclusively on expert male reciters, our model achieves remarkable performance on female recitations (120 samples) and overall error detection.

qdat_bench shows a higher PER of 0.058 (5.8%) on authentic learner recordings, which is expected given the increased complexity of detecting real pronunciation errors and handling variability in learner execution of Tajweed rules. But (5.5%) remains very acceptable despite trained on expert recitations only. Despite this performance gap, the model maintains excellent Tajweed F1 scores (75.8% average) on learner data, demonstrating robust generalization capabilities for practical educational applications. The aggregate Tajweed F1 score of 0.758 represents the mean performance across three key rules: Noon Moshaddadah (0.869), Ikhfaa (0.453), and Qalqalah (0.953). Similarly, the average Madd RMSE of 0.596 encompasses performance across normal madd rules

[7] Available at: https://huggingface.co/datasets/obadx/qdat_bench

Table 5: Test Results on Expert Quranic Recitations. Evaluation conducted on three Mushaf datasets (19.0, 29.0, 30.0) featuring expert male reciters with extensive Tajweed training, recorded under controlled acoustic conditions. The phonemes level demonstrates the highest error rate (0.543%) because it uses the largest vocabulary of 44 characters including padding, making it the most challenging classification task among all representation levels.

Metric	**Value**
loss	0.01162
per_phonemes	0.00543
per_hams_or_jahr	0.00117
per_shidda_or_rakhawa	0.00172
per_tafkheem_or_taqeeq	0.00167
per_itbaq	0.00092
per_safeer	0.00132
per_qalqla	0.00085
per_tikraar	0.0009
per_tafashie	0.0016
per_istitala	0.0008
per_ghonna	0.0013
average_per	**0.0021**

Table 6: qdat_bench Results - Comprehensive Evaluation on Authentic Learner Mistakes. This benchmark builds upon the original qdat dataset Osman et al., 2021 through extensive expert reannotation that systematically labeled each audio segment across multiple dimensions: complete phoneme-level transcription, 10 sifat characteristics, and comprehensive Tajweed rule classifications. The enhanced dataset contains 159 samples (120 female, 39 male reciters) focusing on Quranic verse from Surah Al-Ma'idah (5:109), providing a concentrated evaluation of key pronunciation challenges.

Aggregate Metrics	**Value**
per_phonemes	0.058
avg_per	0.019
avg_tajweed_f1	0.758
avg_tajweed_acc	0.847
avg_madd_rmse	0.596
Tajweed Rules F1	**Value**
Noon Moshaddadah	0.869
Ikhfaa (Noon Mokhfah)	0.453
Qalqalah	0.953
Madd Rules RMSE	**Value**
Normal Madd (5 rules)	0.464
Separate Madd	0.687
Aared Madd	1.034

(0.464), separate madd (0.687), and aared madd (1.034).
Notably, the Ikhfaa F1 score of 0.453 is considerably lower than other rules, which is expected given the acoustic similarity between Ikhfaa and clear noon pronunciation. This challenge affects both human perception and automated detection, as few reciters can reliably distinguish Ikhfaa when it is recited with characteristics similar to noon moshaddah. The model's performance on this rule reflects the inherent difficulty in detecting subtle nasalization differences. Detailed analysis of these patterns and methodology considerations are provided in the appendix 8.5.
Notably, despite being trained exclusively on male expert reciters, our model demonstrates strong generalization capability by achieving 75.8% Tajweed F1 score and 84.7% accuracy on female recitations in qdat_bench, highlighting the robustness of our approach for real-world deployment where diverse learner populations are expected. This performance on authentic learner mistakes validates the practical applicability of our Quranic phonetic script and multi-level CTC architecture. The comprehensive nature of qdat_bench provides a robust foundation for evaluating Quranic pronunciation models.

7 Limitations and Future Work

A big limitation appears from attribute-specific articulation patterns: Certain attributes apply exclusively to individual letters, such as `Istitala` for (ض) and `Tikrar` for (ر). Consequently, we expect our model will be unable to capture instances of (ض) without `Istitala` or (ر) without `Tikrar`. This limitation similarly applies to Tajweed rules that occur less frequently in the Holy Quran, such as `Imala`, `Rawm`, and `Tasheel`. The obious solution is to annotate real data with these errors to make the model understand better these errors.

8 Conclusion

We present a novel approach for assessing pronunciation errors in Holy Quran learners through a multi-level Quran Phonetic Script that captures all pronunciation errors for *Hafs* (except `Ishmam`, as it is a visual diacritic not orally produced). We provide 848 hours of annotated audio data with 286K samples, a 98% automated pipeline for generating similar datasets featuring our Tasmeea verification algorithm, and a novel multi-level CTC model with an 11-level structure (1 phoneme level + 10 sifat levels). Achieving a 0.21% average phoneme error rate on unseen expert test data proves the learnability of the Quran Phonetic Script. Furthermore, our model demonstrates robust generalization on real learner errors through qdat_bench, achieving 75.8% Tajweed F1 score and 84.7% accuracy on female reciters, fundamentally transforming Holy Quran pronunciation assessment methodology.

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References

Abdou, S. M., & Rashwan, M. (2014). A computer aided pronunciation learning system for teaching the holy quran recitation rules. *2014 IEEE/ACS 11th International Conference on Computer Systems and Applications (AICCSA)*, 543–550.

AI, T. (2023). Whisper base arabic quran (automatic speech recognition for quranic recitation) [Model by Tarteel AI. Company website: https://www.tarteel.ai/].

Al-Marri, M., Raafat, H., Abdallah, M., Abdou, S., & Rashwan, M. (2018). Computer aided qur'an pronunciation using dnn. *Journal of Intelligent & Fuzzy Systems*, *34*(5), 3257–3271.

Alqadasi, A. M. A., Zeki, A. M., Sunar, M. S., Salam, M. S. B. H., Abdulghafor, R., & Khaled, N. A. (2023). Improving automatic forced alignment for phoneme segmentation in quranic recitation. *IEEE Access*, *12*, 229–244.

Alsahafi, Y. S., & Asad, M. (2024). Empirical study on mispronunciation detection for tajweed rules during quran recitation. *2024 6th International Conference on Computing and Informatics (ICCI)*, 39–45. https://doi.org/10.1109/ICCI61671.2024.10485145

دار الغوثاني للدراسات القرآنية. التجويد المصور. (2021). أمين رشدس سويد.

[المؤلف: علي الضباع (توفي 0831هـ)] صريح النص في الكلمات المختلف فيها عن حفص. (1380هـ-). علي الضباع.
مكتبة ومطبعة مصطفى البابي الحلبي وأولاده.

مخارج الحروف الصحاح وصفاتها عند الخليل بن أحمد الفراهيدي قراءة في ضوء الدرس. (2023). هبيرة, عز
مجلة جامعة الأمير عبد القادر للعلوم الإسلامية اللساني الحديث., *31*, 165–190. https://doi.org/10.37138/emirj.v31i2.1936

Baevski, A., Zhou, Y., Mohamed, A., & Auli, M. (2020). Wav2vec 2.0: A framework for self-supervised learning of speech representations. *Advances in neural information processing systems*, *33*, 12449–12460.

Barrault, L., Chung, Y.-A., Meglioli, M. C., Dale, D., Dong, N., Duppenthaler, M., Duquenne, P.-A., Ellis, B., Elsahar, H., Haaheim, J., et al. (2023). Seamless: Multilingual expressive and streaming speech translation. *arXiv preprint arXiv:2312.05187*.

Chung, Y.-A., Zhang, Y., Han, W., Chiu, C.-C., Qin, J., Pang, R., & Wu, Y. (2021). W2v-bert: Combining contrastive learning and masked language modeling for self-supervised speech pre-training. *2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, 244–250.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 4171–4186.

[8] https://hpc.bibalex.org/

Graves, A., Fernández, S., Gomez, F., & Schmidhuber, J. (2006). Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks. *Proceedings of the 23rd International Conference on Machine Learning (ICML 2006)*, 369–376. https://doi.org/10.1145/1143844.1143891

Gulati, A., Qin, J., Chiu, C.-C., Parmar, N., Zhang, Y., Yu, J., Han, W., Wang, S., Zhang, Z., Wu, Y., et al. (2020). Conformer: Convolution-augmented transformer for speech recognition. *arXiv preprint arXiv:2005.08100*.

Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. *science*, *313*(5786), 504–507.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences*, *79*(8), 2554–2558.

Jordal, I., & Contributors. (2025). Audiomentations: A python library for audio data augmentation.

Khan, H. I., Abid, A., Moussa, M. M., & Abou-Allaban, A. (2021). The tarteel dataset: Crowd-sourced and labeled quranic recitation.

Kheir, Y. E., Ali, A., & Chowdhury, S. A. (2023). Automatic pronunciation assessment–a review. *arXiv preprint arXiv:2310.13974*.

Kheir, Y. E., Ibrahim, O., Meghanani, A., Almarwani, N., Toyin, H. O., Alharbi, S., Alfadly, M., Alkanhal, L., Selim, I., Elbatal, S., et al. (2025). Towards a unified benchmark for arabic pronunciation assessment: Quranic recitation as case study. *arXiv preprint arXiv:2506.07722*.

Mohammed, A., Sunar, M. S. B., & Salam, M. S. H. (2017). Recognition of holy quran recitation rules using phoneme duration. *International Conference of Reliable Information and Communication Technology*, 343–352.

Omran, D., Fawzi, S., & Kandil, A. (2023a). Automatic detection of some tajweed rules. *2023 20th Learning and Technology Conference (LT)*, 157–160. https://doi.org/10.1109/LT58159.2023.10092350

Omran, D., Fawzi, S., & Kandil, A. (2023b). Automatic detection of some tajweed rules. *2023 20th Learning and Technology Conference (L&T)*, 157–160.

Osman, H. M., Mustafa, B. S., & Faisal, Y. (2021). Qdat: A data set for reciting the quran. *International Journal on Islamic Applications in Computer Science And Technology*, *9*(1), 1–9.

Plaquet, A., & Bredin, H. (2023). Powerset multi-class cross entropy loss for neural speaker diarization. *Proc. INTERSPEECH 2023*.

Putra, B., Atmaja, B. T., & Prananto, D. (2012). Developing speech recognition system for quranic verse recitation learning software. *IJID (International Journal on Informatics for Development)*, *1*(2), 1–8.

Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., & Sutskever, I. (2023). Robust speech recognition via large-scale weak supervision. *International conference on machine learning*, 28492–28518.

Schneider, S., Baevski, A., Collobert, R., & Auli, M. (2019). Wav2vec: Unsupervised pre-training for speech recognition. *arXiv preprint arXiv:1904.05862*.

Shaiakhmetov, D., Gimaletdinova, G., Momunov, K., & Cankurt, S. (2025). Evaluation of the pronunciation of tajweed rules based on dnn as a step towards interactive recitation learning. *arXiv preprint arXiv:2503.23470*.

Sherif, M., Samir, A., Khalil, A., & Mohsen, R. (2007). Enhancing usability of capl system for quran recitation learning.

Team, S. (2024). Silero vad: Pre-trained enterprise-grade voice activity detector (vad), number detector and language classifier.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, *30*, 5998–6008.

Appendix

8.1 Quran Phoneme Script Vocabulary

Table 7: Phoneme Set (43 Symbols)

Phoneme Name	**Symbol**
hamza	ء
baa	ب
taa	ت
thaa	ث
jeem	ج
haa_mohmala	ح
khaa	خ
daal	د
thaal	ذ
raa	ر
zay	ز
seen	س
sheen	ش
saad	ص
daad	ض
taa_mofakhama	ط
zaa_mofakhama	ظ
ayn	ع
ghyn	غ
faa	ف
qaf	ق
kaf	ك
lam	ل
meem	م
noon	ن
haa	ه
waw	و

Continued on next page…

Table 8: Sifat Set (10 Attributes)

Sifat (English)	Sifat (Arabic)	Available Attributes (English)	Available Attributes (Arabic)
hams_or_jahr	الهمس أو الجهر	hams, jahr	همس, جهر
shidda_or_rakhawa	الشدة أو الرخاوة	shadeed, between, rikhw	شديد, بين بين, رخو
tafkheem_or_taqeeq	التفخيم أو الترقيق	mofakham, moraqaq, low_mofakham	مفخم, مرقق, أدنى المفخم
itbaq	الإطباق	monfateh, motbaq	منفتح, مطبق
safeer	الصفير	safeer, no_safeer	صفير, لا صفير
qalqla	القلقلة	moqalqal, not_moqalqal	مقلقل, غير مقلقل
tikraar	التكرار	mokarar, not_mokarar	مكرر, غير مكرر
tafashie	التفشي	motafashie, not_motafashie	متفشي, غير متفشي
istitala	الاستطالة	mostateel, not_mostateel	مستطيل, غير مستطيل
ghonna	الغنة	maghnoon, not_maghnoon	مغنون, غير مغنون

Table 7: Phoneme Set (43 Symbols) – Continued

Phoneme Name	Symbol
yaa	ي
alif	ا
yaa_madd	ۦ
waw_madd	ۥ
fatha	َ
dama	ُ
kasra	ِ
fatha_momala	◊
alif_momala	ـ
hamza_mosahala	أ
qlqla	چ
noon_mokhfah	ں
meem_mokhfah	م
sakt	ۜ
dama_mokhtalasa	ُ

8.2 Uthmani to Phonetic Conversion Operations

The 26 sequential phonetization operations:

1. **DisassembleHrofMoqatta** (تفكيك حروف مقطعة): Separates Quranic initials (e.g., الم، الر) into individual letters.
2. **SpecialCases** (حالات خاصة): Handles special words like يبۜسط that have different pronunciation forms defined in `MoshafAttributes`.
3. **BeginWithHamzatWasl** (البدء بهمزة الوصل): Processes words starting with connecting hamza (ٱ) and converts it to hamza (ء) with appropriate harakah for nouns and verbs.
4. **BeginWithSaken** (البدء بساكن): Manages words beginning with a consonant (sakin) like لْيَقْطَعْ, as Arabic doesn't start utterances with consonants.
5. **ConvertAlifMaksora** (تحويل الألف المقصورة): Converts ى in Uthmani script to either yaa (ي) or alif (ا) based on context.
6. **NormalizeHmazat** (توحيد الهمزات): Standardizes hamza forms (أ إ ؤ ئ) to ء.
7. **IthbatYaaYohie** (إثبات ياء يحيي): Handles words like يُحْيِۦ where two yaa letters occur - resolves conflicts when pausing on words with consecutive consonants (التقاء الساكنين) by adding another yaa at end.
8. **RemoveKasheeda** (إزالة الكشيدة): Deletes elongation marks (ـ) from text.
9. **RemoveHmzatWaslMiddle** (إزالة همزة الوصل الوسطية): Removes connecting hamza (ٱ) in non-initial positions.
10. **RemoveSkoonMostadeer** (حذف الحرف الذي فوقع سكون مستدير): Eliminates letters with circular sukoon diacritics like alif in جَمَعُوا۟.
11. **SkoonMostateel** (سكون مستطيل): Removes alif with elongated sukoon mid-word and adds it at the end during pauses (وقف).
12. **MaddAlewad** (مد العوض): Removes alif after tanween fatha mid-word and adds alif while removing tanween at pause positions (وقف).
13. **WawAlsalah** (واو الصلاة): Replaces letter waw (و) with small alif above combined with alif.
14. **EnlargeSmallLetters** (تكبير الحروف الصغيرة): Resizes miniature Arabic letters to standard proportions.
15. **CleanEnd** (تنظيف النهاية): Removes redundant diacritics and spaces at word endings.
16. **NormalizeTaa** (توحيد التاء): Converts ة (taa marbuta) to ت or ه based on context, and converts final ة to haa (ه).

17. **AddAlifIsmAllah** (إضافة ألف اسم الله): Inserts compensatory alif in derivatives of ”الله”.

18. **PrepareGhonnaIdghamIqlab** (تهيئة الغنة والإدغام والإقلاب): Preprocesses text for nasalization, assimilation, and conversion rules.

19. **IltiqaaAlsaknan** (التقاء الساكنين): Resolves consecutive consonants by inserting vowels.

20. **DeleteShaddaAtBeginning** (حذف الشدة في البداية): Removes shadda (ّ) from word-initial letters.

21. **Ghonna** (غنة): Applies nasalization during pronunciation of sakin noon and tanween.

22. **Tasheel** (تسهيل): Adds a letter representing alif with tasheel easing.

23. **Imala** (إمالة): Converts fatha with imala to `fatha_momala` phoneme and alif with imala to `alif_momala` phoneme.

24. **Madd** (مد): Adds madd symbols for all madd types, inserting `madd_alif` (ا), `madd_waw` (و), and `madd_yaa` (ي).

25. **Qalqla** (قلقة): Adds echoing effect to ق, ط, ب, ج, د letters with sukoon.

26. **RemoveRasHaaAndShadda** (إزالة رأس الحاء علامة السكون): Deletes sukoon diacritic marks.

8.3 Tasmeea Verfication Algorithm

Algorithm 1 Tasmeea Algorithm

```
Require: $text\_segments = [s_1, s_2, \ldots, s_n]$, $sura\_idx$, $overlap\_words = 6$,
    $window\_words = 30$, $acceptance\_ratio = 0.5$, flags for special phrases
Ensure: List of tuples $(match, ratio)$ per segment
$aya \leftarrow 1$ {Start at first verse}
$penalty \leftarrow 0$
for each segment $s_i$ in $text\_segments$ do
    $norm\_text \leftarrow$ normalize($s_i$) {Remove spaces/diacritics}
    $min\_win \leftarrow window\_words - 10$, $max\_win \leftarrow window\_words + 10$
    $start\_range \leftarrow [-(overlap + penalty), (overlap +$
    max$(window\_words, max\_win) + penalty]$
    if first segment and $include\_istiaatha$ then
        Check istiaatha special case
    else if last segment and $include\_sadaka$ then
        Check sadaka special case
    end if
    $best\_ratio \leftarrow 0$, $best\_match \leftarrow$ null
    for each start position $p$ in $start\_range$ do
        for each window size $w \in [min\_win, max\_win]$ do
            $c \leftarrow$ extract candidate at $(aya, p, w)$
            $dist \leftarrow$ edit_distance$(norm\_text, c)$
            $ratio \leftarrow 1 - \min(dist, |norm\_text|)/|norm\_text|$
            if $ratio > best\_ratio$ or $(ratio = best\_ratio$ and $|p| < |best\_start|)$
            then
                update $best\_ratio$, $best\_match$, $best\_start$, $best\_window$
            end if
        end for
    end for
    if $best\_ratio < acceptance\_ratio$ then
        output (null, $best\_ratio$)
        $penalty \leftarrow max\_win$
        $aya \leftarrow aya + 1$ {Default advance}
    else
        output ($best\_match$, $best\_ratio$)
        $aya \leftarrow aya + best\_start + best\_window$
        $penalty \leftarrow 0$
    end if
end for
Complexity: $O(N \cdot W \cdot L^2)$ {$N$=segments, $W$=window size, $L$=segment length}
```

8.4 Moshaf Attribute Definitions

- **rewaya (الرواية)**

  - Values: - `hafs` (حفص)
  - Default Value:
  - More Info: The type of the quran Rewaya.

- **recitation_speed** (سرعة التلاوة)
  - Values:
    - ∗ `mujawad` (مجود)
    - ∗ `above_murattal` (فويق المرتل)
    - ∗ `murattal` (مرتل)
    - ∗ `hadr` (حدر)
  - Default Value: `murattal` (مرتل)
  - More Info: The recitation speed sorted from slowest to the fastest سرعة التلاوة مرتبة من الأبطأ إلي الأسرع

- **takbeer** (التكبير)
  - Values:
    - ∗ `no_takbeer` (لا تكبير)
    - ∗ `beginning_of_sharh` (التكبير من أول الشرح لأول الناس)
    - ∗ `end_of_doha` (التكبير من آخر الضحى لآخر الناس)
    - ∗ `general_takbeer` (التكبير أول كل سورة إلا التوبة)
  - Default Value: `no_takbeer` (لا تكبير)
  - More Info: The ways to add takbeer (الله أكبر) after Istiaatha (استعاذة) and between end of the surah and beginning of the surah. `no_takbeer`: ”لا تكبير” — No Takbeer (No proclamation of greatness, i.e., there is no Takbeer recitation) `beginning_of_sharh`: ”التكبير من أول الشرح لأول الناس” — Takbeer from the beginning of Surah Ash-Sharh to the beginning of Surah An-Nas `end_of_dohaf`: ”التكبير من آخر الضحى لآخر الناس” — Takbeer from the end of Surah Ad-Duha to the end of Surah An-Nas `general_takbeer`: ”التكبير أول كل سورة إلا التوبة” — Takbeer at the beginning of every Surah except Surah At-Tawbah

- **madd_monfasel_len** (مد المنفصل)
  - Values:
    - ∗ 2
    - ∗ 3
    - ∗ 4
    - ∗ 5
  - Default Value:
  - More Info: The length of Mad Al Monfasel ”مد المنفصل” for Hafs Rewaya.

- **madd_mottasel_len** (مقدار المد المتصل)

  - Values:
    - `4`
    - `5`
    - `6`
  - Default Value:
  - More Info: The length of Mad Al Motasel ”مد المتصل” for Hafs.

- **madd_mottasel_waqf** (مقدار المد المتصل وقفا)
  - Values:
    - `4`
    - `5`
    - `6`
  - Default Value:
  - More Info: The length of Madd Almotasel at pause for Hafs.. Example ”السماء”.

- **madd_aared_len** (مقدار المد العارض)
  - Values:
    - `2`
    - `4`
    - `6`
  - Default Value:
  - More Info: The length of Mad Al Aared ”مد العارض للسكون”.

- **madd_alleen_len** (مقدار مد اللين)
  - Values:
    - `2`
    - `4`
    - `6`
  - Default Value: `None`
  - More Info: The length of the Madd al-Leen when stopping at the end of a word (for a sakin waw or ya preceded by a letter with a fatha) should be less than or equal to the length of Madd al-'Arid (the temporary stretch due to stopping). **Default Value is equal to** `madd_aared_len`. مقدار مد اللين عن القوف (للواو الساكنة والياء الساكنة وقبلها حرف مفتوح) ويجب أن يكون مقدار مد اللين أقل من أو يساوي مع العارض

- **ghonna_lam_and_raa** (غنة اللام و الراء)
  - Values:
    - `ghonna` (غنة)

    - `no_ghonna` (لا غنة)
  - Default Value: `no_ghonna` (لا غنة)
  - More Info: The ghonna for merging (Idghaam) noon with Lam and Raa for Hafs.

- **meem_aal_imran** (ميم آل عمران في قوله تعالى: {الم الله} وصلا)
  - Values:
    - `waqf` (وقف)
    - `wasl_2` (فتح الميم ومدها حركتين)
    - `wasl_6` (فتح الميم ومدها ستة حركات)
  - Default Value: `waqf` (وقف)
  - More Info: The ways to recite the word meem Aal Imran (الم الله) at connected recitation. `waqf`: Pause with a prolonged madd (elongation) of 6 harakat (beats). `wasl_2` Pronounce ”meem” with fathah (a short ”a” sound) and stretch it for 2 harakat. `wasl_6` Pronounce ”meem” with fathah and stretch it for 6 harakat.

- **madd_yaa_alayn_alharfy** (مقدار المد اللازم الحرفي للعين)
  - Values:
    - `2`
    - `4`
    - `6`
  - Default Value: `6`
  - More Info: The length of Lzem Harfy of Yaa in letter Al-Ayen Madd ”المد الحرفي اللازم لحرف العين” in surar: Maryam ”مريم”, AlShura ”الشورى”.

- **saken_before_hamz** (الساكن قبل الهمز)
  - Values:
    - `tahqeek` (تحقيق)
    - `general_sakt` (سكت عام)
    - `local_sakt` (سكت خاص)
  - Default Value: `tahqeek` (تحقيق)
  - More Info: The ways of Hafs for saken before hamz. ”The letter with sukoon before the hamzah (ء)”.And it has three forms: full articulation (`tahqeeq`), general pause (`general_sakt`), and specific pause (`local_skat`).

- **sakt_iwaja** (السكت عند عوجا في الكهف)
  - Values:
    - `sakt` (سكت)
    - `waqf` (وقف)

    - `idraj` (إدراج)
  - Default Value: `waqf` (وقف)
  - More Info: The ways to recite the word ”عوجا” (Iwaja). `sakt` means slight pause. `idraj` means not `sakt`. `waqf`: means full pause, so we can not determine whether the reciter uses `sakt` or `idraj` (no sakt).

- **sakt_marqdena** (السكت عند مرقدنا في يس)
  - Values:
    - `sakt` (سكت)
    - `waqf` (وقف)
    - `idraj` (إدراج)
  - Default Value: `waqf` (وقف)
  - More Info: The ways to recite the word ”مرقدنا” (Marqadena) in Surat Yassen. `sakt` means slight pause. `idraj` means not `sakt`. `waqf`: means full pause, so we can not determine whether the reciter uses `sakt` or `idraj` (no sakt).

- **sakt_man_raq** (السكت عند من راق في القيامة)
  - Values:
    - `sakt` (سكت)
    - `waqf` (وقف)
    - `idraj` (إدراج)
  - Default Value: `sakt` (سكت)
  - More Info: The ways to recite the word ”من راق” (Man Raq) in Surat Al Qiyama. `sakt` means slight pause. `idraj` means not `sakt`. `waqf`: means full pause, so we can not determine whether the reciter uses `sakt` or `idraj` (no sakt).

- **sakt_bal_ran** (السكت عند بل ران في المطففين)
  - Values:
    - `sakt` (سكت)
    - `waqf` (وقف)
    - `idraj` (إدراج)
  - Default Value: `sakt` (سكت)
  - More Info: The ways to recite the word ”بل ران” (Bal Ran) in Surat Al Motaffin. `sakt` means slight pause. `idraj` means not `sakt`. `waqf`: means full pause, so we can not determine whether the reciter uses `sakt` or `idraj` (no sakt).

- **sakt_maleeyah** (وجه قوله تعالى {ماليه هلك} بالحاقة)
  - Values:

        - sakt (سكت)
        - waqf (وقف)
        - idgham (إدغام)
    - Default Value: waqf (وقف)
    - More Info: The ways to recite the word {ماليه هلك} in Surah Al-Ahqaf. sakt means slight pause. idgham Assimilation of the letter 'Ha' (ه) into the letter 'Ha' (ه) with complete assimilation.waqf: means full pause, so we can not determine whether the reciter uses sakt or idgham.

- **between_anfal_and_tawba** (وجه بين الأنفال والتوبة)
    - Values:
        - waqf (وقف)
        - sakt (سكت)
        - wasl (وصل)
    - Default Value: waqf (وقف)
    - More Info: The ways to recite end of Surah Al-Anfal and beginning of Surah At-Tawbah.

- **noon_and_yaseen** (الإدغام والإظهار في النون عند الواو من قوله تعالى: {يس والقرآن} و {ن والقلم})
    - Values:
        - izhar (إظهار)
        - idgham (إدغام)
    - Default Value: izhar (إظهار)
    - More Info: Whether to merge noon of both: {يس} and {ن} with (و) "idgham" or not "izhar".

- **yaa_ataan** (إثبات الياء وحذفها وقفا في قوله تعالى {آتان} بالنمل)
    - Values:
        - wasl (وصل)
        - hadhf (حذف)
        - ithbat (إثبات)
    - Default Value: wasl (وصل)
    - More Info: The affirmation and omission of the letter 'Yaa' in the pause of the verse {آتاني} in Surah An-Naml. wasl: means connected recitation without pausing as (آتانيَ). hadhf: means deletion of letter (ي) at pause so recited as (آتان). ithbat: means confirmation reciting letter (ي) at pause as (آتاني).

- **start_with_ism** (وجه البدأ بكلمة {الاسم} في سورة الحجرات)

  - Values:
    - ∗ `wasl` (وصل)
    - ∗ `lism` (لسم)
    - ∗ `alism` (ألسم)
  - Default Value: `wasl` (وصل)
  - More Info: The ruling on starting with the word {الاسم} in Surah Al-Hujurat. `lism` Recited as (لسم) at the beginning. `alism` Recited as (ألسم). `wasl`: means completing recitation without pausing as normal, So Reciting is as (بئس لسم).

- **yabsut** (السين والصاد في قوله تعالى: {والله يقبض ويبسط} بالبقرة)
  - Values:
    - ∗ `seen` (سين)
    - ∗ `saad` (صاد)
  - Default Value: `seen` (سين)
  - More Info: The ruling on pronouncing `seen` (س) or `saad` (ص) in the verse {والله يقبض ويبسط} in Surah Al-Baqarah.

- **bastah** (السين والصاد في قوله تعالى: {وزادكم في الخلق بسطة} بالأعراف)
  - Values:
    - ∗ `seen` (سين)
    - ∗ `saad` (صاد)
  - Default Value: `seen` (سين)
  - More Info: The ruling on pronouncing `seen` (س) or `saad` (ص) in the verse {وزادكم في الخلق بسطة} in Surah Al-A'raf.

- **almusaytirun** (السين والصاد في قوله تعالى {أم هم المصيطرون} بالطور)
  - Values:
    - ∗ `seen` (سين)
    - ∗ `saad` (صاد)
  - Default Value: `saad` (صاد)
  - More Info: The pronunciation of `seen` (س) or `saad` (ص) in the verse {أم هم المصيطرون} in Surah At-Tur.

- **bimusaytir** (السين والصاد في قوله تعالى: {لست عليهم بمصيطر} بالغاشية)
  - Values:
    - ∗ `seen` (سين)
    - ∗ `saad` (صاد)

  - Default Value: `saad` (صاد)
  - More Info: The pronunciation of `seen` (س) or `saad` (ص) in the verse {لست عليهم بمصيطر} in Surah Al-Ghashiyah.

- **tasheel_or_madd** (همزة الوصل في قوله تعالى: {آلذكرين} بموضعي الأنعام و{آلآن} موضعي يونس و{آلله} بيونس والنمل)
  - Values:
    - `tasheel` (تسهيل)
    - `madd` (مد)
  - Default Value: `madd` (مد)
  - More Info: Tasheel of Madd ”وجع التسهيل أو المد” for 6 words in The Holy Quran: ”ءالذكرين”, ”ءالله”, ”ءائن”.

- **yalhath_dhalik** (الإدغام وعدمه في قوله تعالى: {يلهث ذلك} بالأعراف)
  - Values:
    - `izhar` (إظهار)
    - `idgham` (إدغام)
    - `waqf` (وقف)
  - Default Value: `idgham` (إدغام)
  - More Info: The assimilation (`idgham`) and non-assimilation (`izhar`) in the verse {يلهث ذلك} in Surah Al-A’raf. `waqf`: means the reciter has paused on (يلهث)

- **irkab_maana** (الإدغام والإظهار في قوله تعالى: {اركب معنا} بهود)
  - Values:
    - `izhar` (إظهار)
    - `idgham` (إدغام)
    - `waqf` (وقف)
  - Default Value: `idgham` (إدغام)
  - More Info: The assimilation and clear pronunciation in the verse {اركب معنا} in Surah Hud. This refers to the recitation rules concerning whether the letter ”Noon” (ن) is assimilated into the following letter or pronounced clearly when reciting this specific verse. `waqf`: means the reciter has paused on (اركب)

- **noon_tamnna** (الإشمام والروم (الاختلاس) في قوله تعالى {لا تأمنا على يوسف})
  - Values:
    - `ishmam` (إشمام)
    - `rawm` (روم)
  - Default Value: `ishmam` (إشمام)

  - More Info: The nasalization (`ishmam`) or the slight drawing (`rawm`) in the verse {لا تأمنا على يوسف}

- **harakat_daaf** (حركة الضاد (فتح أو ضم) في قوله تعالى {ضعف} بالروم)
  - Values:
    - `fath` (فتح)
    - `dam` (ضم)
  - Default Value: `fath` (فتح)
  - More Info: The vowel movement of the letter ’Dhad’ (ض) (whether with `fath` or `dam`) in the word {ضعف} in Surah Ar-Rum.

- **alif_salasila** (إثبات الألف وحذفها وقفا في قوله تعالى: {سلاسلا} بسورة الإنسان)
  - Values:
    - `hadhf` (حذف)
    - `ithbat` (إثبات)
    - `wasl` (وصل)
  - Default Value: `wasl` (وصل)
  - More Info: Affirmation and omission of the ’Alif’ when pausing in the verse {سلاسلا} in Surah Al-Insan. This refers to the recitation rule regarding whether the final ”Alif” in the word ”سلاسلا” is pronounced (affirmed) or omitted when pausing (waqf) at this word during recitation in the specific verse from Surah Al-Insan. `hadhf`: means to remove alif (ا) during pause as (سلاسل) `ithbat`: means to recite alif (ا) during pause as (سلاسلا) `wasl` means completing the recitation as normal without pausing, so recite it as (سلاسلَ وأغلالا)

- **idgham_nakhluqkum** (إدغام القاف في الكاف إدغاما ناقصا أو كاملا {نخلقكم} بالمرسلات)
  - Values:
    - `idgham_kamil` (إدغام كامل)
    - `idgham_naqis` (إدغام ناقص)
  - Default Value: `idgham_kamil` (إدغام كامل)
  - More Info: Assimilation of the letter ’Qaf’ into the letter ’Kaf,’ whether incomplete (`idgham_naqis`) or complete (`idgham_kamil`), in the verse {نخلقكم} in Surah Al-Mursalat.

- **raa_firq** (التفخيم والترقيق في راء {فرق} في الشعراء وصلا)
  - Values:
    - `waqf` (وقف)
    - `tafkheem` (تفخيم)
    - `tarqeeq` (ترقيق)

  - Default Value: `tafkheem` (تفخيم)
  - More Info: Emphasis and softening of the letter ’Ra’ in the word {فرق} in Surah Ash-Shu’ara’ when connected (wasl). This refers to the recitation rules concerning whether the letter ”Ra” (ر) in the word ”فرق” is pronounced with emphasis (`tafkheem`) or softening (`tarqeeq`) when reciting the specific verse from Surah Ash-Shu’ara’ in connected speech. `waqf`: means pausing so we only have one way (tafkheem of Raa)

- **raa_alqitr** (التفخيم والترقيق في راء {القطر} في سبأ وقفا)
  - Values:
    - `wasl` (وصل)
    - `tafkheem` (تفخيم)
    - `tarqeeq` (ترقيق)
  - Default Value: `wasl` (وصل)
  - More Info: Emphasis and softening of the letter ’Ra’ in the word {القطر} in Surah Saba’ when pausing (waqf). This refers to the recitation rules regarding whether the letter ”Ra” (ر) in the word ”القطر” is pronounced with emphasis (`tafkheem`) or softening (`tarqeeq`) when pausing at this word in Surah Saba’. `wasl`: means not pausing so we only have one way (tarqeeq of Raa)

- **raa_misr** (التفخيم والترقيق في راء {مصر} في يونس وموضعي يوسف والزخرف وقفا)
  - Values:
    - `wasl` (وصل)
    - `tafkheem` (تفخيم)
    - `tarqeeq` (ترقيق)
  - Default Value: `wasl` (وصل)
  - More Info: Emphasis and softening of the letter ’Ra’ in the word {مصر} in Surah Yunus, and in the locations of Surah Yusuf and Surah Az-Zukhruf when pausing (waqf). This refers to the recitation rules regarding whether the letter ”Ra” (ر) in the word ”مصر” is pronounced with emphasis (`tafkheem`) or softening (`tarqeeq`) at the specific pauses in these Surahs. `wasl`: means not pausing so we only have one way (tafkheem of Raa)

- **raa_nudhur** (التفخيم والترقيق في راء {نذر} بالقمر وقفا)
  - Values:
    - `wasl` (وصل)
    - `tafkheem` (تفخيم)
    - `tarqeeq` (ترقيق)
  - Default Value: `tafkheem` (تفخيم)

  - More Info: Emphasis and softening of the letter 'Ra' in the word {نذر} in Surah Al-Qamar when pausing (waqf). This refers to the recitation rules regarding whether the letter "Ra" (ر) in the word "نذر" is pronounced with emphasis (`tafkheem`) or softening (`tarqeeq`) when pausing at this word in Surah Al-Qamar. `wasl`: means not pausing so we only have one way (tarqeeq of Raa)

- **raa_yasr** (التفخيم والترقيق في راء {يسر} بالفجر و{أن أسر} بطه والشعراء و{فأسر} بهود والحجر والدخان وقفا)
  - Values:
    - `wasl` (وصل)
    - `tafkheem` (تفخيم)
    - `tarqeeq` (ترقيق)
  - Default Value: `tarqeeq` (ترقيق)
  - More Info: Emphasis and softening of the letter 'Ra' in the word {يسر} in Surah Al-Fajr when pausing (waqf). This refers to the recitation rules regarding whether the letter "Ra" (ر) in the word "يسر" is pronounced with emphasis (`tafkheem`) or softening (`tarqeeq`) when pausing at this word in Surah Al-Fajr. `wasl`: means not pausing so we only have one way (tarqeeq of Raa)

- **meem_mokhfah** (هل الميم مخفاة أو مدغمة)
  - Values:
    - `meem` (ميم)
    - `ikhfaa` (إخفاء)
  - Default Value: `ikhfaa` (إخفاء)
  - More Info: This is not a **standard** Hafs way but a disagreement between **scholars** in our century on how to **pronounce Ikhfa** for meem. Some **scholars** do full merging (إدغام) and the others open the **lips** a little bit (إخفاء). We did not want to add this, but some of the best reciters disagree about this.

8.5 QDat Bench Dataset

QDat Bench is a comprehensive benchmark dataset for evaluating model performance in processing Quranic audio recordings with focus on Tajweed rules. This dataset builds upon the original qdat dataset Osman et al., 2021 after extensive reannotation and enhancement to include all Tajweed rules and QPS 3 (complete phoneme-level annotations and 10 sifat (characteristic) levels).

The enhanced dataset provides F1 and MSE metrics for Tajweed rules, enabling researchers to compare different representations and approaches to Tajweed rule detection. This comprehensive annotation framework makes qdat_bench particularly valuable for advancing research in automated Quranic pronunciation assessment and error detection.

The dataset addresses several limitations of the original qdat collection. The original dataset suffered from incomplete coverage of all Tajweed rules, with only partial implementation of the comprehensive rule set required for thorough evaluation. Additionally, the original collection contained multiple reciters recording the same verse (each reciter records the same verse 10 times), creating significant redundancy and potential bias in evaluation. In contrast, qdat_bench selects a single recording randomly for every reciter. Finally, the original dataset lacked comprehensive phoneme-level and sifat-level annotations, limiting its utility for fine-grained analysis of pronunciation patterns and characteristics.

QDat Bench contains 159 samples focusing on the verse: قَالُوا۟ لَا عِلْمَ لَنَآ إِنَّكَ أَنتَ عَلَّٰمُ ٱلْغُيُوبِ from Surah Al-Ma'idah (5:109), providing a concentrated evaluation of key Tajweed rules.

8.5.1 Data Structure

The dataset encompasses several key components designed for comprehensive analysis of Quranic recitation patterns. Each entry contains an audio file recorded in mono channel format, a unique identifiers for each element, reciter gender (male or female) and age, enabling analysis of pronunciation patterns across different population segments. The phonetic_transcript and sifat fields contain the complete transcription in Quran Phonetic Script (QPS) as described in Section 3, Along with Tajweed rules columns to enable different Tajweed representations benchmark on qdat_bench. Below is description of Tajweed rules found on our benchmark:

8.5.1.1 Madd (Prolongation) Rules: The dataset includes comprehensive annotations for various types of Madd rules, which are fundamental to proper Quranic recitation. The normal Madd rules are captured through several specific metrics: `qalo_alif_len` measures the length of normal Madd alif in the word قالوا on a scale of 0-8, while `qalo_waw_len` similarly measures the normal Madd waw in the same word. Additional normal Madd measurements include `laa_alif_len` for the normal Madd alif in لا and `allam_alif_len` for the normal Madd alif in علام. The Separate Madd is measured through `separate_madd`, which captures the length for the phrase لنا إنك (0-8). Finally, Madd Aared, is evaluated using `madd_aared_len`, measuring prolongation before sukoon (0-8), which typically exhibits the highest variability in implementation.

8.5.1.2 Ghunnah (Nasalization) Rules: Ghunnah rules are systematically annotated to capture the nasalization characteristics essential for proper Quranic pronunciation. The `noon_moshaddadah_len` metric evaluates the length of noon moshaddadah in the word إنَّك using a binary classification system where 0 indicates partial nasalization and 1 represents complete implementation. Similarly, the `noon_mokhfah_len` measures the Ikhfaa pronunciation in أنت through a three-tiered system: 0 represents a clear noon pronunciation, 1 indicates partial Ikhfaa implementation, and 2 denotes complete Ikhfaa execution.

8.5.1.3 Qalqalah (Echo) Rules: The Qalqalah rule is captured through the `qalqalah` metric, which identifies the presence or absence of the echo characteristic in the word

الغيوب. This binary classification system uses 0 to indicate no Qalqalah implementation and 1 to denote proper Qalqalah execution.

8.5.2 *Dataset Statistics*

The qdat_bench dataset comprises 159 carefully selected samples. The demographic distribution reflects a diverse participant pool, with 120 female reciters representing 75.5% of the dataset and 39 male reciters accounting for 24.5%. The age diversity across various age groups provides comprehensive coverage of different learning stages and pronunciation patterns as shown in Figure 7. The benchmark has various types of error: 106 reciters have one or more errors while 53 have complete correct recitations as shown in Figure 8. Finally Figure 9 shows the errors per every Tajweed rule as red represents errors and green with correct recitation.

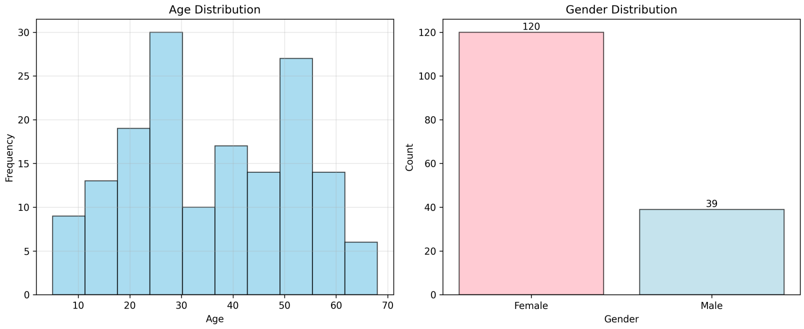

Figure 7: Age and gender distribution of qdat_bench reciters, showing diverse demographic coverage with 75.5% female and 24.5% male participants across different age groups.

8.5.3 *Evaluation Results*

The detailed evaluation results on qdat_bench are presented in the following tables, showing performance across different Tajweed rule categories and metrics.

8.5.4 *Performance Analysis and Discussion*

The benchmark has many limitations: the size is very limited with imbalanced gender. Along with not all Tajweed rules covered like (Tasheel). Neither all phonemes like letter thaal: ذ. But it is a move towards benchmarking Tajweed rules.

8.5.5 *Usage*

The dataset can be loaded using the Hugging Face datasets library:

```
from datasets import load_dataset
ds = load_dataset('obadx/qdat_bench')
print(ds['train'][0])  # Display first sample
```

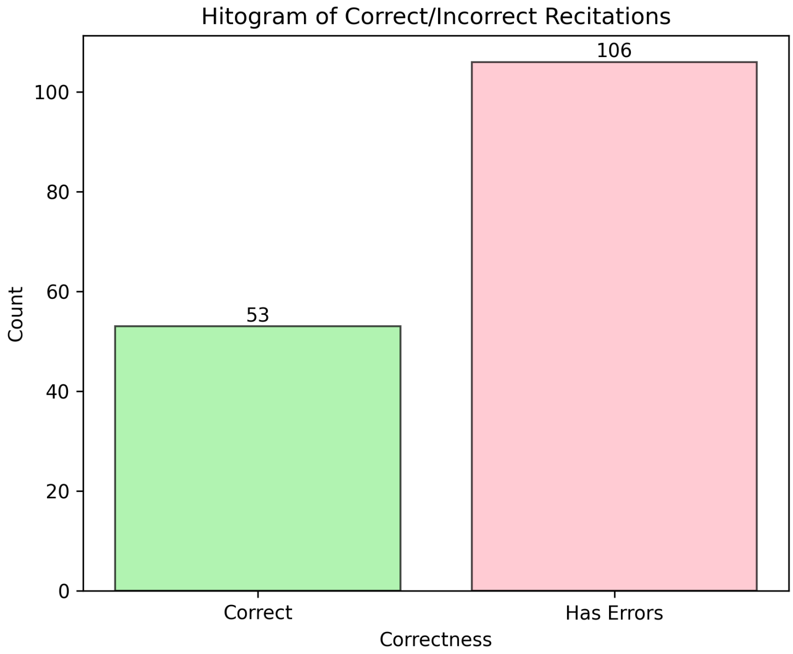

Figure 8: Distribution of recitation correctness across different Tajweed rules in the benchmark: red represents a reciter has one or more errors and green with correct recitation.

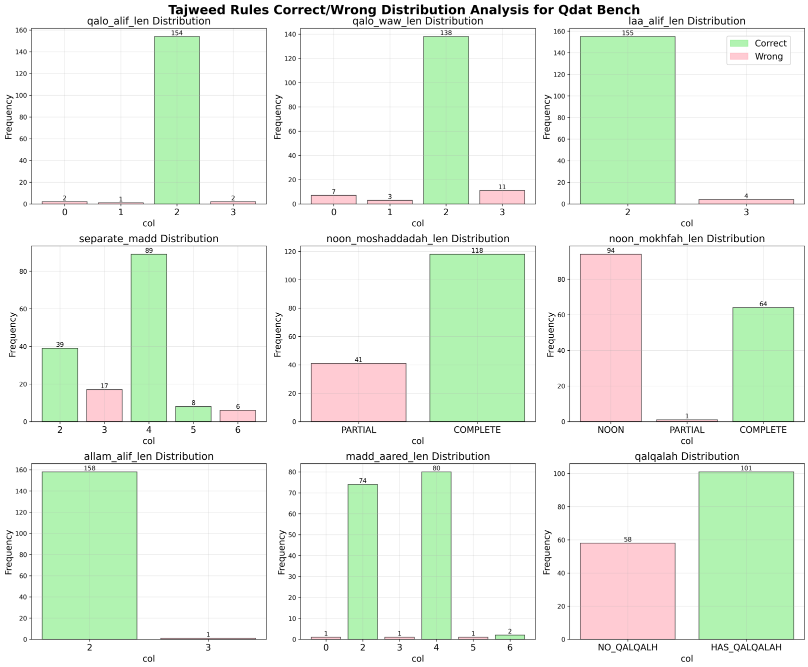

Figure 9: Tajweed rules coverage histogram showing the frequency and diversity of rules evaluated in the benchmark dataset, red bars represents errors and green with correct recitation.

Table 9: Detailed QDat Bench Speech Metrics

Metric	Value
per_phonemes	0.058
per_hams_or_jahr	0.017
per_shidda_or_rakhawa	0.031
per_tafkheem_or_taqeeq	0.022
per_itbaq	0.012
per_safeer	0.010
per_qalqla	0.011
per_tikraar	0.013
per_tafashie	0.016
per_istitala	0.009
per_ghonna	0.014
average_per	0.019

Table 10: QDat Bench Madd Rules Performance (RMSE). Golden values are for madd are: (2 for normal madd, 2 or 4 for separate madd, and 2, 4, or 6 for aared madd.

Madd Rule	RMSE
qalo_alif_len (normal)	0.449
qalo_waw_len (normal)	0.456
laa_alif_len (normal)	0.404
separate_madd (separate)	0.687
allam_alif_len (normal)	0.549
madd_aared_len	1.034
Average Madd RMSE	0.596

Table 11: QDat Bench Noon Moshaddadah Performance

Metric	Partial	Complete	Average
Recall	0.659	1.000	0.829
Precision	1.000	0.894	0.947
F1 Score	0.794	0.944	0.869
Accuracy		0.912	

Table 12: QDat Bench Noon Mokhfah Performance

Metric	Noon	Partial	Complete
Recall	0.468	0.000	0.984
Precision	1.000	0.000	0.568
F1 Score	0.638	0.000	0.720
Average F1		0.453	
Accuracy		0.673	

Table 13: QDat Bench Qalqalah Performance

Metric	**No Qalqalah**	**Has Qalqalah**
Recall	0.966	0.950
Precision	0.918	0.980
F1 Score	0.941	0.965
Macro F1	0.953	
Accuracy	0.956	