Learning meters of Arabic and English poems with Recurrent Neural Networks: a step forward for language understanding and synthesis

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***Abstract*—Recognizing a piece of writing as a poem or prose is usually easy for the majority of people; however, only specialists can determine which meter a poem belongs to. In this paper, we build Recurrent Neural Network (RNN) models that can classify poems according to their meters from plain text. The input text is encoded at the character level and directly fed to the models without feature handcrafting. This is a step forward for machine understanding and synthesis of languages in general, and Arabic language in particular.**

Among the 16 poem meters of Arabic and the 4 meters of English the networks were able to correctly classify poem with an overall accuracy of 96.38% and 82.31% respectively. The poem datasets used to conduct this research were massive, over 1.5 million of verses, and were crawled from different nontechnical sources, almost Arabic and English literature sites, and in different heterogeneous and unstructured formats. These datasets are now made publicly available in clean, structured, and documented format for other future research.

To the best of the authors' knowledge, this research is the first to address classifying poem meters in a machine learning approach, in general, and in RNN featureless based approach, in particular. In addition, the dataset is the first publicly available dataset ready for the purpose of future computational research.

***Index Terms*—Poetry, Meters, Al-'arud, Arabic, English, Recurrent Neural Networks, RNN, Deep Learning, Deep Neural Networks, DNN, Classification, Text Mining.**

I. Introduction

A. Arabic Language

Arabic is the fifth most widely spoken language [13]. It is written from right to left (RTL). Its alphabet consists of 28 primary letters and 8 further derived letters from the primary ones, which makes all letters sum up to 36. The writing system is cursive; hence, most letters are joined and a few letters remain disjoint.

Diacritics	*without*	*fat-ha*	*dam-ma*	*kas-ra*	*sukun*
writing	د	دَ	دُ	دِ	دْ
short vowel	—	*/a/*	*/u/*	*/i/*	*/no vowel/*

Table I: *The 4 Diacritics of Arabic Language. Transliterated names (1st row), writing style on example letter* د (2nd row), and corresponding short pronunciation vowel (3rd row).

Each Arabic letter represents a consonant, which means that short vowels are not represented by the 36 letters. For this reason the need rises for *diacritics*, which are symbols "decorating" original letters. Usually, a *diacritic* is written above or under the letter to emphasize the short vowel accompanied with that letter. There are 4 diacritics: ◌َ ◌ُ ◌ِ ◌ْ. Table I lists these 4 diacritics on an example letter د, their transliterated names, along with their short vowel representation. Each of the three diacritics ◌َ ◌ُ ◌ِ is called *harakah*; whereas the fourth ◌ْ is called *sukun*. Diacritics are just to make short vowels clearer; however, their writing is not compulsory since they can be almost inferred from the grammatical rules and the semantic of the text. Moreover, a phrase with diacritics written for only some letters is linguistically sound.

There are two more sub-diacritics made up of the basic four. The first is known as *shaddah* ◌ّ, which must associate with one of the three *harakah* and written as ◌َّ ◌ُّ ◌ِّ. *Shaddah* is a shorthand writing for the case when a letter appears two times in a row where the first occurrence is accompanied with *sukun* and the second occurrence is accompanied with *harakah*. Then, for short, it is written as one occurrence accompanied with *shaddah* associated with the corresponding *harakah*. E.g., دْدَ is written as دَّ. The second is known as *tanween*, which must associate as well one of the three *harakah* and written as: ◌ٍ ◌ٌ ◌ً. *Tanween* accompanies the last letter of some words, according to Arabic grammar, ending with *harakah*. This is merely for reminding the reader to pronounce the word as if there is نْ (sounding as */n/*), follows that *harakah*. However, it is just a phone and is not a part of the word itself. E.g., رَجُلٌ is pronounced نْ + رَجُلُ and رَجُلٍ is pronounced نْ + رَجُلِ.

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Foot	فَعُوْلُنْ	فَاْعِلُنْ	مُسْتَفْعِلُنْ	مَفَاْعِيْلُنْ	مَفْعُوْلَاْتُ	فَاْعِلَاْتُنْ	مُفَاْعَلَتُنْ	مُتَفَاْعِلُنْ
Scansion	0/0//	0//0/	0//0/0/	0/0/0//	/0/0/0/	0/0//0/	0///0//	0//0///

Table II: The eight feet of Arabic poetry. Every digit (/ or 0) represents the corresponding diacritic over a letter of a feet: *harakah* (◌َ ◌ُ ◌ِ) or *sukun* (◌ْ) respectively. Any of the three letters و ا ى (called *mad*) is equivalent to 0; *tanween* and *shaddah* are equivalent to 0/ and /0 respectively.

B. Arabic Poetry (الشعر العربي)

Arabic poetry is the earliest form of Arabic literature; it dates back to the sixth century. Poets wrote poems without knowing exactly what rules make a collection of words a poem. People recognize poetry by nature, but only talented ones who could write poems. This was the case until *Al-Farahidi* (718 – 786 CE) has analyzed Arabic poems and recognized their patterns. He came up with that the succession of consonants and vowels, and hence *harakah* and *sukun*, rather than the succession of letters themselves, produces patterns (*meters*) which keeps the balanced music of pieces of poem. He recognized fifteen meters. Later, one of his students, *Al-khfash*, discovered one more meter to make them all sixteen. Arabs call meters بحور, which means "seas" [11].

A poem is a collection of verses. A verse example is:

قفا نبك من ذِكرى حبيب ومنزل   بِسقطِ اللِّوى بينَ الدَّخول فحَوْملِ

A verse, known in Arabic as *bayt* (بيت), which consists of two halves. Each half is called a *shatr* (شطر). *Al-Farahidi* has introduced *al-'arud* (العروض), which is often called the *Knowledge of Poetry* or the study of poetic meters. He laid down rigorous rules and measures, with them we can determine whether a meter of a poem is sound or broken. For the present article to be fairly self-contained, where many details are reduced, a very brief introduction to *al-'arud* is provided through the following lines.

A meter is an ordered sequence of phonetic syllables (blocks or mnemonics) called *feet*. A foot is written with letters only having *harakah* or *sukun*, i.e., with neither *shaddah* nor *tanween*; and hence each letter in a foot maps directly to either a consonant or a vowel. Therefore, feet represent phonetic mnemonics, of the pronounced poem, called *tafa'il* (تفاعيل). Table II lists the eight feet used by Arabs and the pattern (scansion) of *harakah* and *sukun* of each foot, where a *harakah* is represented as / and a *sukun* is represented as 0. Each scansion reads RTL to match the letters of the corresponding foot.

According to *Al-Farahidi* and his student, they discovered sixteen combinations of *tafa'il* in Arabic poems; they called each combination a *meter* (بحر). (Theoretically speaking, there is no limit for either the number of *tafa'il* or their combinations; however, Arab composed poems using only this structure). A meter appears in a *verse* twice, once in each *shatr*. E.g., وَيَسْأَلُ فِي الحَوَادِثِ ذو صَوابِ is the first *shatr* of a verse of *Al-Wafeer* meter مُفَاْعَلَتُنْ مُفَاْعَلَتُنْ فَعُوْلُنْ. The pattern of the *harakah* and *sukun* of this meter is 0/0// 0///0// 0///0// (RTL), and is obtainable directly by replacing each of the three feet by the corresponding code in table II. This pattern corresponds exactly to the pattern of *harakah* and *sukun* of the pronounced (not written) *shatr*. E.g., the pronunciation of the first two words and the first two letters of the third word وَيَسْأَلُ فِي الْ has exactly the same pattern as the first of the three *tafa'il* of the meter مُفَاْعَلَتُنْ, and both have the scansion 0///0//. For more clarification, the colored parts have corresponding pronunciation pattern; which emphasizes that the start and end of a word do not have to coincide with the start and end of the phonetic syllable. The pronunciation of the rest of the *shatr* حوادث ذو صواب maps to the rest of the meter مفاعلتن فعولن. Any other poem, regardless of its wording and semantic, following the same meter, i.e., following the same pattern of *harakah* and *sukun*, will have the same pronunciation or phonetic pattern.

Meter Name	Pattern	Scansion
al-Taweel	فَعُوْلُنْ مَفَاْعِيْلُنْ فَعُوْلُنْ مَفَاْعِلُنْ	0//0// 0/0// 0/0/0// 0/0//
al-Kamel	مُتَفَاْعِلُنْ مُتَفَاْعِلُنْ مُتَفَاْعِلُنْ	0//0/// 0//0/// 0//0///
al-Baseet	مُسْتَفْعِلُنْ فَاْعِلُنْ مُسْتَفْعِلُنْ فَاْعِلُنْ	0//0/ 0//0/0/ 0//0/ 0//0/0/
al-Khafeef	فَاْعِلَاْتُنْ مُسْتَفْعِلُنْ فَاْعِلَاْتُنْ	0/0//0/ 0//0/0/ 0/0//0/
al-Wafeer	مُفَاْعَلَتُنْ مُفَاْعَلَتُنْ فَعُوْلُنْ	0/0// 0///0// 0///0//
al-Rigz	مُسْتَفْعِلُنْ مُسْتَفْعِلُنْ مُسْتَفْعِلُنْ	0//0/0/ 0//0/0/ 0//0/0/
al-Raml	فَاْعِلَاْتُنْ فَاْعِلَاْتُنْ فَاْعِلَاْتُنْ	0/0//0/ 0/0//0/ 0/0//0/
al-Motakarib	فَعُوْلُنْ فَعُوْلُنْ فَعُوْلُنْ فَعُوْلُنْ	0/0// 0/0// 0/0// 0/0//
al-Sar'e	مُسْتَفْعِلُنْ مُسْتَفْعِلُنْ مَفْعُوْلَاْتُ	/0/0/0/ 0//0/0/ 0//0/0/
al-Monsareh	مُسْتَفْعِلُنْ مَفْعُوْلَاْتُ مُسْتَفْعِلُنْ	0//0/0/ /0/0/0/ 0//0/0/
al-Mogtath	مُسْتَفْعِلُنْ فَاْعِلَاْتُنْ فَاْعِلَاْتُنْ	0/0//0/ 0/0//0/ 0//0/0/
al-Madeed	فَاْعِلَاْتُنْ فَاْعِلُنْ فَاْعِلَاْتُنْ	0/0//0/ 0//0/ 0/0//0/
al-Hazg	مَفَاْعِيْلُنْ مَفَاْعِيْلُنْ	0/0/0// 0/0/0//
al-Motadarik	فَاْعِلُنْ فَاْعِلُنْ فَاْعِلُنْ فَاْعِلُنْ	0//0/ 0//0/ 0//0/ 0//0/
al-Moktadib	مَفْعُوْلَاْتُ مُسْتَفْعِلُنْ مُسْتَفْعِلُنْ	0//0/0/ 0//0/0/ /0/0/0/
al-Modar'e	مَفَاْعِيْلُنْ فَاْعِلَاْتُنْ فَاْعِلَاْتُنْ	0/0//0/ 0/0//0/ 0/0/0//

Table III: The sixteen meters of Arabic poem: transliterated names (1st col.), mnemonics or *tafa'il* (2nd col.), and the corresponding pattern of *harakah* and *sukun* in 0/ format or scansion (3rd col.).

Table III lists the names of all the sixteen meters, the transliteration of their names, and their patterns (scansion). Each pattern is written in two equivalent forms: the feet style using the eight feet of Table II and the scansion pattern using the 0/ symbols. The scansion is written in groups; each corresponds to one foot and all are RTL.

C. English poetry

English poetry dates back to the seventh century. At that time poems were written in *Anglo-Saxon*, also known as *Old English*. Many political changes have influenced the language until it became as it is nowadays. English prosody was not formalized rigorously as a stand-alone knowledge, but many tools of the *Greek* prosody were borrowed to describe it.

A *syllable* is the unit of pronunciation having one vowel, with or without surrounding consonants. English words consist of one or more syllables. For example the word "water" (pronounced as /ˈwɔːtə(r)/) consists of two phonetic syllables: /ˈwɔː/ and /tə(r)/. Each syllable has only one vowel sound. Syllables can be either stressed or un-

Foot	*Iamb*	*Trochee*	*Dactyl*	*Anapest*	*Pyrrhic*	*Amphibrach*	*Spondee*
Stresses	×/	/×	/××	××/	××	×/×	//

Table IV: The seven feet of English poem. Every foot is a combination of stressed and unstressed syllables, denoted by / and *x* respectively.

stressed and will be denoted by / and × respectively. In phonology, a stress is a phonetic emphasis given to a syllable, which can be caused by, e.g., increasing the loudness, stretching vowel length, or changing the sound pitch. In the previous "water" example, the first syllable is stressed, which means it is pronounced with high sound pitch; whereas the second syllable is unstressed which means it is pronounced in low sound pitch. Therefore, "water" is a stressed-unstressed word, which can be denoted by /×. Stresses are shown in the phonetic script using the primary stress symbol (ˈ). There are seven different combinations of stressed and unstressed syllables that make the seven poetic *feet*. They are shown in table IV. Meters are described as a sequence of feet. English meters are *qualitative* meters, which are stressed syllables coming at regular intervals. A meter is defined as the repetition of one of the previous seven feet one to eight times. If the foot is repeated once, then the verse is *monometer*, if it is repeated twice then it is a *dimeter* verse, and so on until *octameter* which means a foot is repeated eight times. This is an example, where stressed syllables are bold: "That **time** of **year** thou **mayst** in **me** be**hold**". The previous verse belongs to the *Iamb* meter, with the pattern ×/ repeated five times; so it is an *Iambic pentameter* verse.

D. Paper Organization

The rest of this paper is organized as follows. Sec. II is a literature review of meter detection of both languages; the novelty of our approach and the point of departure from the literature will be emphasized. Sec. III explains the data acquisition steps and the data repository created by this project to be publicly available for future research; in addition, this section explains character encoding methods, along with our new encoding method and how they are applied to Arabic letters in particular. Sec. IV explains how experiments are designed and conducted in this research. Sec. V presents and interprets the results of these experiments. Sec. VI is a discussion, where we emphasize the interpretation of some counter-intuitive results and connect them to the size of conducted experiments, and the remedy in the future work that is currently under implementation.

II. Literature review

To the best of our knowledge, the problem addressed in the present paper has never been addressed in the literature. "Learning" poem style from text so that machines are able to classify unseen written poem to the right meter seems to be a novel area. However, there is some literature on recognizing the meters of written Arabic poem using rule-based deterministic algorithms. We did not find related work on English written poem. These rules are derived by humans/experts and not learned by machines from data. In this regard, this is quite irrelevant to our present problem, and this is our point of departure in this research. However, we review these methods for the sake of completion.

Ref.	**Accuracy**	**Test Size**	**Poem**
[4]	75%	128	Arabic
[1]	82.2%	417	
This article	96.38%	150,000	
This article	82.31%	1,740	English

Table V: Overall accuracy of this article compared to literature.

[10] worked on the Ottoman Language. They converted the Ottoman text into a lingual form; in particular, the poem was transliterated to Latin transcription alphabet (LTA). Next, the text was fed to the algorithm, which uses a database containing all Ottoman meters, to be compared to the existing meters and then classified to the closest one.

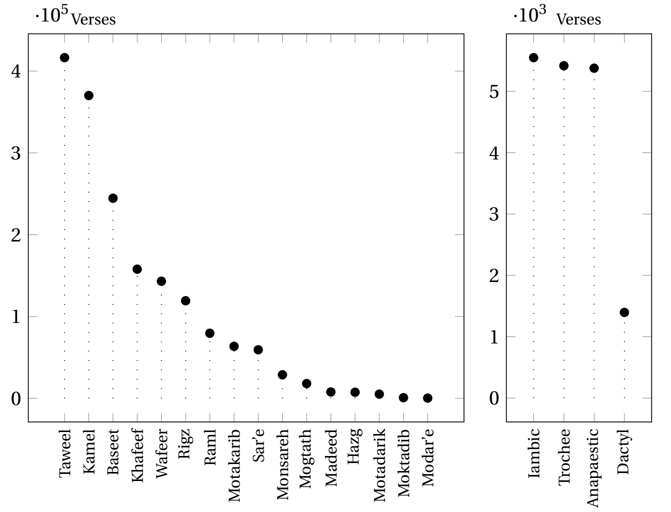
[4] worked on Arabic language. They formalized the *scansion*s, *al-'arud*, and some lingual rules (like pronounced and silent rules, which are directly related to *harakah* and *sukun*) in terms of context-free grammar and regular expression templates. The classification accuracy was only 75% on a very small sample of 128 verses.

[1] worked on Arabic language. They designed a five-step deterministic *algorithm* for analyzing and detecting meters. First, they input text carrying full diacritics for all letters. Second, they convert the input text into *al-'arud* writing style (Sec. I-B) using `if-else` rules. Third, the metrical *scansion* rules are applied, which leaves the input text as a sequence of zeros and ones. Fourth, each group of zeros and ones are defined as a *tafa'il* (Table II). Finally, the input text is classified to the closest meter to the *tafa'il* sequence (Table III). The classification accuracy of this algorithm is 82.2%, on a relatively small sample of 417 verses.

It is quite important to observe that although these algorithms are deterministic rules that are fed by experts, alas, they did not succeed in producing high accuracy, 75% and 82.2%. This is in contrast to our featureless RNN approach that remarkably outperforms these methods by achieving 96.38%. The interpretation of that is clear. The rule-based algorithms cannot list all possible combinations of anomalies in written text, including missing diacritics on some characters, breaking the meter by a poet, etc; whereas, RNN will be able to "learn" by example the probability of these occurrences. Table V summarizes the accuracies and the testing sample size of this literature in comparison with our approach. It is even more surprising that while these algorithms must work on poem with diacritics, RNN accuracy only dropped about 1% when trained on plain poem with no diacritics.

III. Datasets: Acquisition, Encoding, and Repository

Sec. III-A explains how the Arabic and English datasets were scraped from different non-technical web sources;



(a) *Arabic Dataset* (b) *English Dataset*

Figure 1: Class size (number of verses), of both Arabic and English datasets, ordered descendingly on y axis vs. corresponding meter name on x axis.

and hence needed a lot of cleaning and structuring. For future research on these datasets, and probably for collecting more poem datasets, we launched the data repository "Poem Comprehensive Dataset (PCD)" [14] that is publicly available for the whole community. The datasets on this repository are in their final clean formats and ready for computational purposes. Sec. III-B explains the data encoding at the character level before feeding to the RNN.

A. Arabic and English Datasets Acquisition

We have scrapped the Arabic dataset from two big poetry websites [3, 7]; then both are merged into one large dataset. The total number of verses is 1,862,046. Each verse is labeled by its meter, the poet who authored it, and the age it belongs to. Overall, there are 22 meters, 3701 poets and 11 ages: Pre-Islamic, Islamic, Umayyad, Mamluk, Abbasid, Ayyubid, Ottoman, Andalusian, the era between Umayyad and Abbasid, Fatimid, and modern. We are only interested in the 16 classic meters which are attributed to *Al-Farahidi*. These meters comprise the majority of the dataset with a total number of 1,722,321 verses. Figure 1-a is an ordered bar chart of the number of verses per meter. It is important to mention that the state of verse diacritic is inconsistent; a verse can carry full, partial, or no diacritics. This should affect the accuracy results as discussed in Sec. VI.

The English dataset is scraped from many different web resources [9]. It consists of 199,002 verses; each of them is labeled with one of the four meters: *Iambic*, *Trochee*, *Dactyl* and, *Anapaestic*. Since the *Iambic* class dominates the dataset with 186,809 verses, we downsampled it to 5550 verses to keep classes almost balanced. Figure 1-b is an ordered bar chart of the number of verses per meter.

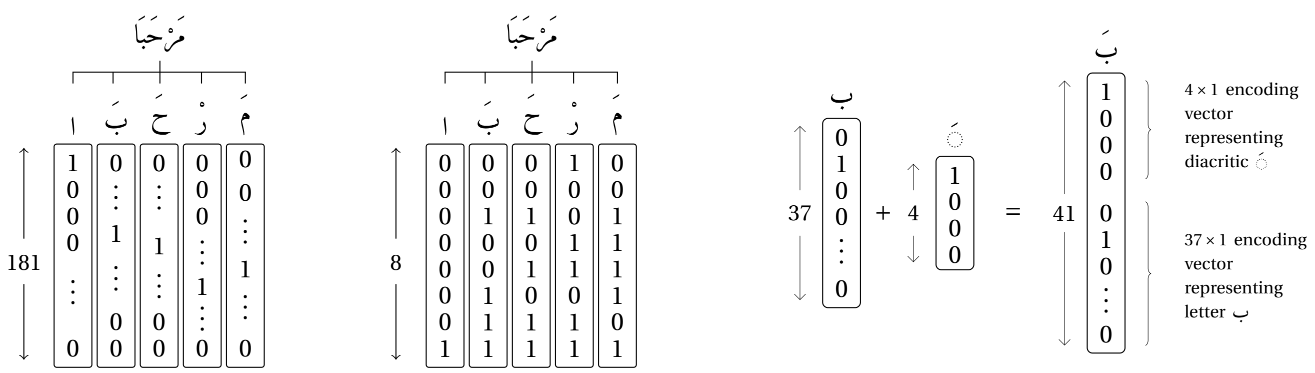
For both Arabic and English datasets, data cleaning was tedious but necessary step before direct computational use. The poem contained non-alphabetical characters, unnecessary in-text white spaces, redundant glyphs, and inconsistent diacritics. E.g., the Arabic dataset in many places contained two consecutive *harakah* on the same letter or a *harakah* after a white space. In addition, as a pre-encoding step, we have factored a letter having either *shaddah* or *tanween* into two letters, as explained in Sec. I-A. This step shortens the encoding vector and saves more memory as explained in the next section. Each of the Arabic and English datasets, after merging and cleaning, is labeled and structured in its final format that is made publicly available [14] as introduced above.

B. Data Encoding

It was introduced in Sec. I-B that a poem meter, in particular Arabic poem, is a phonetic pattern of vowels and consonants that is inferred from *harakah* and *sukun* of the written text. It is therefore obvious that text should be fed to the network at the character (not word) level. Characters are categorical predictors, and therefore character encoding is necessary for feeding them to any form of Neural Networks (NN). Categorical variable encoding has an impact on the neural network performance. (We elaborate on that upon discussing the results in Sec. VI). E.g., [12] is a comparative study for six encoding techniques. They have trained NN on the *car evaluation* dataset after encoding the seven ordered qualitative features. [2] shows that representations of data learned from character-based neural models are more informative than the ones from hand-crafted features.

In this research, we have used the two known encoding schemes *one-hot* and *binary*, in addition to the *two-hot* that we introduced for more efficient encoding of the Arabic letters. Before explaining these three encoding schemes, we need to make the distinction clear among: letters, diacritics, characters (or symbols), and encoding vectors. In English language (and even in Latin that has letters with diacritics, e.g., *ê, é, è, ë, ē, ĕ, ě*), each letter is considered a standalone character (or symbol) with a unique Unicode. Each of them is encoded to a vector, whose length n depends on the encoding scheme. Then, a word, or a verse, consisting of p letters (or characters in this case) would be represented as $n \times p$ matrix. However, in Arabic Language, diacritics are treated differently in the Unicode system. A diacritic is considered a standalone character (symbol) with a unique Unicode (in contrast to Latin diacritics as just explained). E.g., the Arabic letter بَ, which is the letter ب accompanied with the diacritic ◌َ, is considered in Unicode system as two consecutive characters, the character ب followed by the character ◌َ, where each has its own Unicode. Based on that, Arabic and English text are encoded using each of the three encoding methods as follows.

1) One-Hot encoding: In English, there are 26 letters, a white-space, and an apostrophe; hence, there are 28 final characters. In *one-hot* encoding each of the 28 characters will be represented by a vector of length $n = 28$ having a single one and 27 zeros; hence, this is a sparse encoding.


مَرْحَبَا
ا
بَ
حَ
رْ
مَ
181
8
37
4
41
4 × 1 encoding vector representing diacritic ◌َ
37 × 1 encoding vector representing letter ب

(a) *One-Hot*

(b) *Binary*

(c) *Two-Hot*

Figure 2: Three encoding schemes: *One-hot* (a), *binary* (b), and *two-hot* (c). The example word مَرْحَبَا consists of 5 letters and is used to illustrate the *one-hot* and *binary* encodings. One of its letters بَ is selected as an example to illustrate the *two-hot* encoding (c).

In Arabic, we will represent a combination of a letter and its diacritic together as a single encoding vector. Since, from Sec. I-A, there are 36 letters, 4 diacritics and a white-space, and since a letter may or may not have a diacritic whereas the white-space cannot, there is a total of $36\times(4+1)+1 = 181$ combinations. Hence, the encoding vector length is $n = 181$; each vector will have just a single one and 180 zeros.

2) Binary Encoding: In binary encoding, an encoding vector of length n contains a unique binary combination in contrast to the sparse *one-hot* encoding representation. Therefore, the encoding lengths of English and Arabic are $\lceil \log_2 28 \rceil = 5$ and $\lceil \log_2 181 \rceil = 8$ respectively, which is a huge reduction in dimensionality. However, this will be on the expense the challenge added to find the best network architecture design that is capable of decoding this scheme (Sec. VI).

3) Two-Hot encoding: For Arabic language, where diacritics explode the length of the *one-hot* encoding vector to 181, we introduce this new encoding. In this encoding, the 36 letters and the white-space on a hand and the 4 diacritics on the other hand are encoded separately using two *one-hot* encoding vectors of lengths $n = 37$ and $n = 4$ respectively. The final *two-hot* encoding of a letter with a diacritic is the stacking of the two vectors to produce a final encoding vector of length $n = 37+4 = 41$. Clearly, a letter with no diacritic will have 4 zeros in the diacritic portion of the encoding vector.

Figure 2 illustrates the three encoding schemes. The *one-hot* and *binary* encoding of the whole 5-letter word مَرْحَبَا are illustrated as 181×5 and 8×5 matrices respectively (Figures 2-a, 2-b). In Figure 2-c only the second letter of the word, بَ, is taken an example to illustrate the *two-hot* encoding. It is obvious that the *one-hot* is the most lengthy encoding; however, it is straightforward for networks to decode since no two vectors share the same position of '1'. On the other extreme, the *binary* encoding is most economic one; however, networks may need careful design to decode the pattern since vectors share many positions of '1's and '0's. Efficiently, the new designed *two-hot* encoding is almost 28% of the size of *one-hot* encoding.

IV. Experiments

In this section, we explain the design and parameters of all experiments conducted in this research. The number of experiments is the cross product of data representation parameters and network configuration parameters.

A. Data Representation Parameters

For Arabic dataset representation, there are three parameters: *diacritics* (2 values), *trimming* (2 values), and *encoding* (3 values); and hence there are 12 different data representations (the x-axis of Figure 4). A poem can be fed to the network with/without *diacritics* (1D/0D for short); this is to study their effect on network learning. It is anticipated that it will be much easier for the network to learn with *diacritics* since it provides more information on pronunciation and phonetics. Arabic poem data, as indicated in Figure 1-a, is not balanced. To study the effect of this unbalance, the dataset is used once with *trimming* the smallest 5 meters from the dataset and once in full (no trimming), i.e., with all 16 meters presented (1T and 0D for short). There are three different *encoding* methods, *one-hot*, *binary*, and *two-hot* (OneE, BinE, TwoE for short), as explained in Sec. III-B. Although all carry the same information, it is expected that a particular encoding may be suitable for the complexity of a particular network configuration. (see Sec. VI for elaboration).

For English dataset representation, there is no *diacritics* and the dataset does not suffer a severe imbalance (Figure 1-a). Therefore, there are just 2 different data representations, corresponding solely to *one-hot* and *binary* encodings (the x-axis of Figure 7-a).

B. Network Configuration Parameters

The main Recurrent Neural Network (RNN) architectures experimented in this research are: the Long Short Term Memory (LSTM) introduced in [8], the Gated Recurrent Unit (GRU) [5], and their bidirectional variants Bi-LSTM and Bi-GRU. Conceptually, GRU is almost the same as

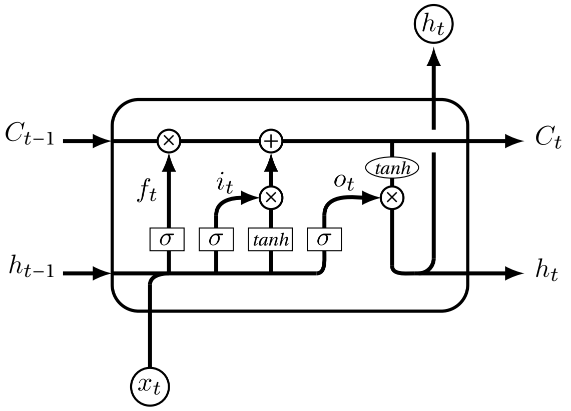


Figure 3: Architecture of a single LSTM cell, the building block of LSTM RNN. (Figure adapted from [6])

the LSTM; however, GRU has less architectural complexity, and hence a fewer number of training parameters. From benchmarks and literature results, it is not clear which of the four architectures is the overall winner. However, for their comparative complexity, it can be anticipated that both LSTM and Bi-LSTM (will be always written as (Bi-)LSTM for short) may be more accurate than their two counterparts (Bi-)GRU on much larger datasets and vice-versa.

We will give a very brief account for LSTMs, which was designed to solve the long-term dependency problem. The other three architectures have the same design flavor and the interested reader can refer to their literature. In theory, RNNs are capable of handling long-term dependencies. However, in practice they do not, due to the *exploding gradient* problem, where weights are updated by the gradient of the loss function with respect to the current weights in each training epoch. In some cases, the gradient may become infinitesimally small, which prevents weights from changing and may stop the network from further learning. LSTMs are designed to be a remedy for this problem. Figure 3 (adapted from [6]) shows an LSTM cell, where: f_t is the forgetting gate, i_t is the input gate, o_t is the output gate, C_t is the memory across cells, W_j, U_j, b_j, $j \in \{f, i, o\}$ are the weight matrices and bias vector. The cell hidden representation h_t of x_t is computed as follows:

$$\begin{aligned}
f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_t),\\
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i),\\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o),\\
C_t &= f_t \circ c_{t-1} + i_t \circ \tanh(W_c x_t + U_c h_{t-1} + b_c),\\
h_t &= o_t \circ \tanh(c_t).
\end{aligned}$$

Next, we detail the network configuration parameters of all experiments. For Arabic dataset, there are four parameters: *cell* (2 values), *layers* (2 values), *size* (2 values), and *weighting* (2 values). Therefore, there are 16 different network configurations to run on each of the 12 data representations above. This results in $16 \times 12 (= 192)$ different experiments (or models). For *cell*, we tried both LSTM and Bi-LSTM. Ideally, GRU and Bi-GRU should be experimented as well. However, this would require almost the double of execution time, which would not be practical for the research life time. This is deferred to another large scale comprehensive research currently running (Sec. VI). We tried 4 and 7 *layers*, with internal vectorized *size* of 50 and 82. Finally, another alternative to *trimming* small classes (meters) that was discussed above, in data representation parameters (Sec. IV-A), is to keep all classes but with *weighting* the loss function to account for the relative class size. For that purpose, we introduce the following *weighting* function:

$$w_c = \frac{1/n_c}{\sum_{c'} 1/n_{c'}}, \tag{1}$$

where n_c is the sample size of class c, $c = 1, 2, \ldots C$, and C is the total number of classes (16 meters in our case).

For English dataset, there are four parameters: *cell* (4 values), *layers* (6 values), *size* (4 values). We did not include *weighting* since the dataset does not suffer sever unbalance as is the case for the Arabic dataset. Therefore, there are 96 different network configurations to run on each of the 2 data representations above. This results in the same number of 192 different experiments (96×2) as those of the Arabic dataset. For *cell*, we had the luxury to experiment with the four types (Bi-)LSTM and (Bi-)GRU, since the dataset is much smaller than the Arabic dataset. For *layers*, we tried $3, 4, \ldots, 8$, each with internal vectorized *size* of 30, 40, 50, and 60.

For all the 192 experiments on Arabic dataset and the 192 experiments on English dataset, networks are trained using dropout of 0.2, batch size of 2048, with Adam optimizer, and 10% for each of validation and testing sets. Experiments are conducted on a Dell Precision T7600 Workstation with Intel Xeon E5-2650 32x 2.8GHz CPU, 64GB RAM, 2 × NVIDIA GeForce GTX TITAN X (Pascal) GPUs; and with: Manjaro 17.1.12 Hakoila OS, x86_64 Linux 4.18.9-1-Manjaro Kernel.

V. Results

The results of all the 192 experiments on Arabic dataset and the 192 experiments on the English dataset are presented and discussed; for each dataset, we start with the overall accuracy followed by the individual accuracy on each class (meter).

A. Results of Arabic dataset

1) Overall Accuracy: First, we explain how Figure 4 presents the overall accuracy of the 16 network configurations (y-axis) for each of the 12 data representations (x-axis). The x-axis is divided into 4 strips corresponding to the 4 combinations of *trimming* × *diacritic* represented as {0T(left), 1T(right)} × {0D(unshaded),1D(shaded)}. Then, each strip includes the 3 different values of *encoding* {BinE, OneE, TwoE}. For each of the 12 data representations, the y-axis represents a rug plot of the accuracy of the 16 experiments; (some values are too small, and hence omitted from the figure). For each rug plot, the highest

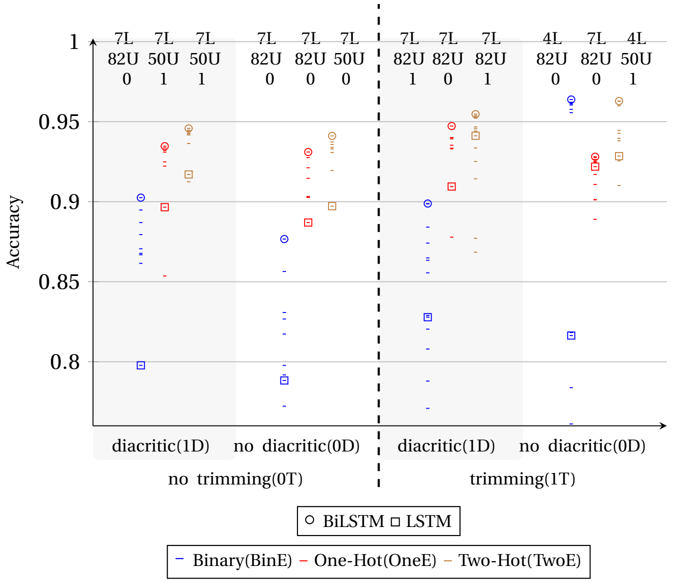


Figure 4: Overall accuracy of the 192 experiments plotted as 12 vertical rug plots (one at each data representation: {0T, 1T} × {0D, 1D} × {OneE, BinE, TwoE}); each represents 16 exp. (for network configurations: {4L, 7L} × {82U, 50U} × {0W, 1W} × {LSTM, BiLSTM}). For each rug plot the best model of each of the two cell types—(Bi-)LSTM—is labeled as circle and square respectively. BiLSTM always wins over the LSTM; and its network configuration parameters are listed at the top of each rug plot.

(Bi-)LSTM accuracies are labeled differently as circle and square respectively; and the network configuration of both of them is listed at the top of the rug plot. To explain the figure, we take as an example the most-left vertical rug plot, which corresponds to (0T, 1D, BinE) data representation. The accuracies of the best (Bi-)LSTM are 0.9025 and 0.7978 respectively. The configuration of the former is (7L, 82U, 0W). Among all the 192 experiments, the highest accuracy is 0.9638 and is possessed by (4L, 82U, 0W) network configuration on (1T, 0D, BinE) data representation.

Next, we discuss the effect of each data representation and network configuration parameter on accuracy. The effect of *trimming* is clear; for particular *diacritic* and *encoding*, the accuracies at 1T are consistently higher than those at 0T. E.g., the highest accuracy at (1T, 0D, TwoE) and (0T, 0D, TwoE) are 0.9629 and 0.9411 respectively. The only exception, with a very little difference, is (1T, 1D, BinE) vs. (0T, 1D, BinE). The effect of *diacritic* is obvious only at 0T (the left half of the Figure), where, at particular *encoding*, the accuracy is higher at 1D than at 0D. However, for 1T, this observation is only true for OneE. This result is counter-intuitive if compared to what is anticipated from the effect of diacritics. We think that this result is an artifact for the small number of network configurations. (More on that in Sec. VI). The effect of *encoding* is clear as well; by looking at each individual strip out of the four strips on the x-axis, accuracy is consistently highest for OneE and TwoE than BinE—the only exception is at (1T, 0D, BinE) that performs better than the other two encodings. It seems that TwoE makes it easier for networks to capture the patterns in data. However, we believe that there is a particular network architecture for each encoding that is capable of capturing the same pattern with yielding the same accuracy; yet, the set of experiments should be conducted at higher resolution of the network configuration parameters space (Sec. VI).

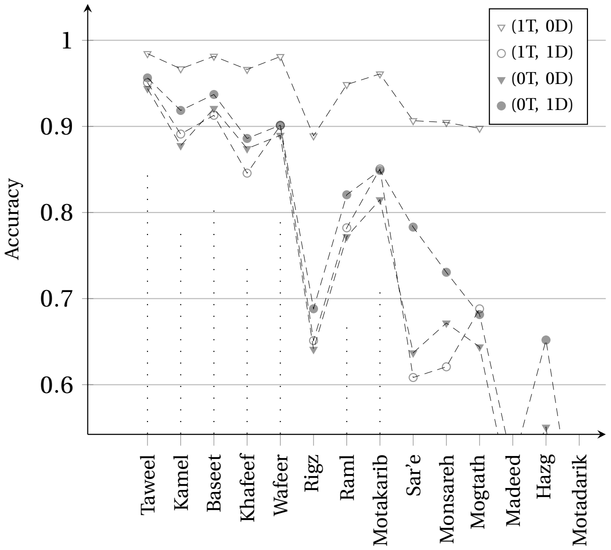


Figure 5: The per-class accuracy for the best four models: {0T, 1T} × {0D, 1D}; the x-axis is sorted by class size as in Figure 1. There is a descending trend with the class size, with the exception at *Rigz* meter.

Next, we comment on the effect of network configuration parameters. For *cell* type, it is obvious that for each data representation, the highest BiLSTM accuracy (circle) is consistently higher than the highest LSTM accuracy (square). This is what is expected from the more complex architecture of the BiLSTM on such a large dataset. For *layers*, the more complex networks of 7 layers achieved the highest accuracies, except for (1T, 0D, BinE) and (1T, 0D, TwoE). The straightforward interpretation for that is the reduction in dataset size occurred by (1T, 0D) combination, which needed less complex network. For cell *size* and loss *weighting*, the figure shows no consistent effect on accuracy.

2) Per-Class (Meter) Accuracy: Next, we investigate the per-class accuracy. For each of the four combinations of *trimming* × *diacritic*, we select the best accuracy out of the three possible encodings. From Figure 4, it is clear that all of them will be at TwoE, except (1T, 0D, BinE), which is the best overall model as discussed above.

Figure 5 displays the per-class accuracy of these four models. The class names (meters) are ordered on the x-axis according to their individual class size (the same order of Figure 1). Several comments are in order. The overall accuracy of each of the four models is around 0.95 (Figure 4); however, for the four models the per-class accuracy of only 6 classes is around this value. For some classes the accuracy drops significantly. Moreover, the common trend for the four models is that the per-class accuracy decreases with the class size for the first 11 classes. Then, the accuracy of the two models with *trimming* keeps decreasing significantly for the remaining 5 classes.

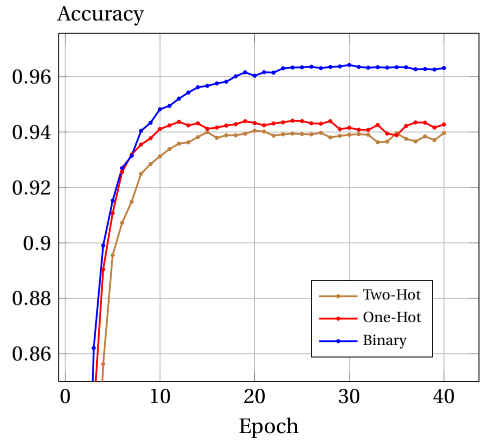


Figure 6: Encoding effect on learning rate of the best model configurations (1T, 0D, 4L, 82U, 0W) with each of the three encodings.

Although this trend is associated with class size, this could only be correlations without causation. This phenomenon, along with what was concluded above for the inconsistent effect of loss *weighting*, emphasize the importance of a more prudent design of the *weighting* function. In addition, the same full set of experiments can be re-conducted with enforcing all classes to have equal size to assert/negate the causality assumption (Sec. VI).

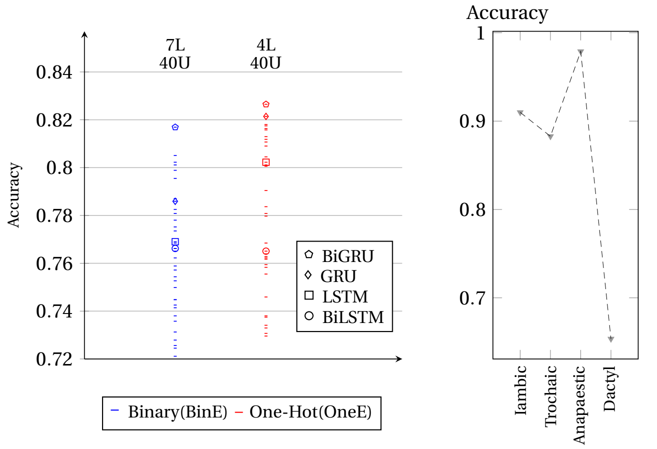
3) Encoding Effect on Learning rate and Memory Utilization: Figure 6-a shows the learning curve of the best model (4L, 82U, 0W, 1T, 0D, BinE), which converges to 0.9638, the same value displayed on Figure 4. The Figure displays, as well, the learning curve of the same model and parameters but with using the other two encodings. The Figure shows no big difference in convergence speed among different encodings.

B. Results of English Dataset

The result presentation and interpretation for the experiments on English dataset are much easier because of the absence of *diacritic*, *trimming*, and loss *weighting* parameters. The relative size of the two datasets has to be brought to attention; from Figure 1, there is almost a factor of 100 in favor of the Arabic dataset.

1) Overall Accuracy: Similar to Figure 4, Figure 7-a displays the accuracy of 96 network configurations (y-axis) for each of the 2 dataset representations (x-axis). The Figure shows that the highest accuracy, 0.8265, is obtained using (4L, 40U, OneE), and BiGRU network. The *encoding* is the only parameter for data representation. OneE achieves higher accuracy than, but close to, BinE. Once again, we anticipate that experimenting with more network configuration should resolve this difference (Sec. VI).

For Network configuration parameters, we start with the *cell* type. At each encoding, the best accuracy of each *cell* type in descending order is: BiGRU, GRU, LSTM, then BiLSTM. (Bi-)GRU models may by more suitable for this smaller size dataset. For *layers*, the best models on OneE was 3L and on BinE was 7L. In contrast to the Arabic dataset, the simple 4L achieved a better accuracy than the complex 7L, with no clear effect of cell *size*. (More discussion on that in Sec. VI).



(a) *Overall accuracy*

(b) *Per-class Accuracy*

Figure 7: Accuracy of experiments on English dataset. (a) Overall accuracy of the 192 experiments plotted as 2 vertical rug plots (one at each data representation: {OneE, BinE}); each represents 96 exp. (for network configurations: {3L, 4L, 5L, 6L, 7L, 8L} × {30U, 40U, 50U, 60U} × {LSTM, BiLSTM, GRU, BiGRU}). For each rug plot the best model of each of the four cell types—(Bi-)LSTM and (Bi-)GRU—is labeled differently. Consistently, the BiGRU was the winner, and its network configuration parameters are listed at the top of each rug plot. (b) The per-class accuracy for the best model of the 192 experiments; the x-axis is sort by the class size as in Figure 1. No particular trend with the class size is observed.

2) Per-Class (Meter) Accuracy: Figure 7-b is a per-class accuracy for the best model (4L, 40U, OneE, BiGRU); the meters are ordered on the x-axis descendingly with the class size as in Figure 1-b. It is clear that class size is not correlated with accuracy. Even for the smallest class, Dactyl, its size is almost one third the Iambic class (Figure 1-b), which is not a huge skewing factor. A more reasonable interpretation is this. Dactyl meter is pentameter or more; while other meters have less repetitions. This makes Dactyl verses very distant in character space from others. And since the network will train to optimize the overall accuracy, this may be on the expense on the class that is both small in size and setting distant in feature space from others. (More discussion on that in Sec. VI).

VI. Discussion

In this section, we will elaborate on the interpretation of some results, reflect on some concepts, and connect to the current and future research.

Sec. III-B explained the three different encoding methods leveraged in this research and cited some literature on the effect of encoding on network accuracy. Mathematically speaking, encoding is seen as feature transformation $\mathcal{T}$, where a character X is transformed to $\mathcal{T}(X)$ in the new encoding space. Since the lossless encoding is invertible, it is clear for any two functions (networks) and any two encodings (transformations) that $\eta_1(\mathcal{T}_1(X)) = \left(\eta_1 \cdot \mathcal{T}_1 \cdot \mathcal{T}_2^{-1}\right)(\mathcal{T}_2(X)) = \eta_2(\mathcal{T}_2(X))$. This means that if the network η_1 is the most accurate network for the encoding $\mathcal{T}_1$, using another encoding $\mathcal{T}_2$ for the same problem requires designing another network $\eta_2 = \eta_1 \cdot \mathcal{T}_1 \cdot \mathcal{T}_2^{-1}$. However, this network may be of complicated architecture to be able to "decode" a terse or complex pattern $\mathcal{T}_2(X)$. The behavior of the three encodings BinE, OneE, and TwoE in this paper can be seen in the light of this discussion. The most terse representation is the BinE ($n = 8$) and the most sparse representation is the OneE ($n = 181$); and in between comes our TwoE ($n = 41$) as a smart design and compromise between the low dimensionality of BinE and the self-decoded nature of the OneE (Sec. III-B). This may be a qualitative interpretation to why the accuracy of the best models was always possessed by the TwoE, yet with one exception at the BinE (Sec. V-A). However, from Figures 4 and 7, the rug plots reveal that the populations of accuracy at different encodings do interleave and each encoding can perform better than others at some experiments. We emphasize that this effect is an artifact to the non exhaustive network configuration parameters and experiments conducted in this research. Had we covered the configuration parameter space then all encoding methods would produce the same accuracy, yet at different network architectures, as each encoding requires the right network architecture to learn from (or to "decode").

Sec. IV-B detailed the network configuration parameters for both Arabic datasets ({4L, 7L} × {82U, 50U} × {0W, 1W} × {LSTM, BiLSTM} = 16 networks) and for English dataset ({3L, 4L, 5L, 6L, 7L, 8L} × {30U, 40U, 50U, 6U} × {LSTM, BiLSTM, GRU, BiGRU} = 96 networks). Each experiment runs almost in one hour (30 epochs × 2 min/epoch) on the mentioned hardware (Sec. IV). The total run time of all network configurations on all data representations for both Arabic and English datasets was $16 \times 12 + 96 \times 2 = 384$ hours, i.e., more than two weeks! We are currently working on more exhaustive set of experiments to cover a good span of the network configuration parameter space to both confirm the above discussion on encoding and to boost the per-class accuracy on both datasets.

The per-class accuracy for both datasets needs investigation; in particular, the interesting trend between the per-class accuracy and the class size of the Arabic dataset needs more investigation. We speculate that this is a mere correlation that does not imply causation; and the reason for this trend may be attributed to the difficulty of, or the similarity between, the meters having small class size. This difficulty, or similarity, may be what is responsible for the low accuracy (Figure 5) on a hand, and the lack of interest of poets to compose at these meters, which resulted in their scarcity (Figure 1), on the other hand.

Diacritic effect is explained in Sec. V; experiments with diacritics scored higher than those without diacritics only when small class size were trimmed from the datasets (1T). When including the whole dataset (0T) the effect of diacritics was not consistent. This interesting phenomenon needs more investigation, since the phonetic pattern of any meter is uniquely identified by diacritics (Sec. I-B). This may be connected to the observation above of the per-class accuracy.

For more investigation of both phenomena, we are working on a randomized-test-like experiments in which all classes will be forced to have equal size n. We will study how the per-class accuracy or overall accuracy, along with their two individual components (precision and recall), behave and how the diacritic effect changes in terms of both n and the number of involved classes k, where $2 \leq k \leq K$, and $K (= 16)$ is the total number of meters.

VII. Conclusion

This paper aimed at training Recurrent Neural Networks (RNN) at the character level on Arabic and English written poem to learn and recognize their meters that make poem sounding rhetoric or phonetic when pronounced. This can be considered a step forward for language understanding, synthesis, and style recognition. The datasets were crawled from several non technical online sources; then cleaned, structured, and published to a repository that is made publicly available for scientific research. To the best of our knowledge, using Machine Learning (ML) in general and Deep Neural Networks (DNN) in particular for learning poem meters and phonetic style from written text, along with the availability of such a dataset, is new to literature.

For the computational intensive nature and time complexity of RNN training, our network configurations were not exhaustive to cover a very wide span of training parameter configurations (e.g., number of layers, cell size, etc). Nevertheless, the classification accuracy obtained on the Arabic dataset was remarkable, specially if compared to that obtained from the deterministic and human derived rule-based algorithms available in literature. However, the door is opened to many questions and more exploration; to list a few: how to increase the accuracy on English dataset, why diacritic effect is not consistent, and why some meters possess low per-class accuracy.

VIII. Acknowledgment

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