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An LSTM –based approach for predicting the next word in Arabic language

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ABSTRACT

Next word prediction, or language modeling, is a crucial task in natural language processing (NLP) that streamlines the typing process by recommending the subsequent word, hence saving time during conversations. The method of next word prediction is intricate, as the machine must anticipate the user's thoughts. A recurrent neural network (RNN), specifically Long Short-Term Memory (LSTM), comprehends previous text and forecasts subsequent words, aiding the user in sentence construction. This study seeks to employ RNN, specifically LSTM, to forecast the subsequent word in one of the most intricate languages with limited resources (Arabic). The results indicated an accuracy of 97.49% and loss of 0.5155%, suggesting that it is sufficiently effective for predicting subsequent Arabic words.

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1. Introduction

The special field of NLP, consists of a number of algorithms and techniques, the purpose of which is to teach the machine to understand the human language, as it is not an easy task because human languages are numerous and very varied and ambiguous. In NLP prediction refers to the guessing of the missing letter, word or sentence [1]. Next word prediction is the phenomenon of guessing with regards to words that have a high possibility of occurrence in a sequence of words or within a particular part of a piece of writing [2]. Pre-type the following word and avoid typing errors [3]. Next word prediction has been used in many fields such as correcting words, word spell check and mobile applications, it has many applications, and it can assist those who never get their words right, therefore next word prediction would be very necessary [4, 5]. The problematic feature of Arabic language is that, it is Semitic language which is more complex and multi-morphological bases than the English language, a highly inflexed language and this further complicated the morphology [6, 7]. Among the possible types of algorithms, there is the language model that can be utilized to predict the likelihood of the next word and the context within which similar words and phrases can occur [8]. NLP model is also advanced to a superior technology into Deep learning algorithms, like Recurrent Neural Network (RNN) and Long Short-Term Memory Network (LSTM) [9]. Deep learning is a subfield of artificial intelligence that takes care of the algorithms that simulate human brain in its data processing or a network that learns by data as well it is popularly referred to as deep neural network [10].

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The reason behind this is that deep neural networks are very functional as they can extract high-level features of the data that they are introduced to upon statistical learning of a large population to provide a useful representation. This goes against the previous finding that includes features that are handmade and as the name suggests [1]. RNN can be made to give the subsequent word relying on the context of the preceding sentences. RNN models are trained (fed) with word and word fed was taken as input layer and a set of hidden units were trained to provide prediction at the output layer of the probability of the next word. The reason is that the hidden layer is reiterated to recurrent context layer after presentation of a word. By so doing, the network acquires a computationally concrete short-term memory [11]. Long Short-Term Memory (LSTM) is a deep-learning architecture that is a continuation of the recurrent neural network architecture [3]. The primary advantage of LSTM is that the technology is able to comprehend the previous text and predict the next words and assist users to construct sentences, by recalling the context of a long succession of words. This property is found with the use of forget gates and is used to address the issue of the vanishing gradient [12, 5]. In summary, next word prediction enhances accuracy and efficiency of NLP-based applications, thus, enhancing user experience and allowing text data manipulation. LSTM will be used in our study to forecast the next word in the Arabic language. The paper has the following structure: Section 2 contains the review of similar works, and section 3 gives the data set. Section 4 outlines the suggested methodology. The findings are discussed in section 5. The main conclusions are presented in section 6.

1.1. Challenges of Arabic language

The fifth language that is most popular in the world is Arabic language. It is native to over 422 million people and is second language to about 250 million people [13]. The Arabic language has 28 letters in the alphabet. The writing in Arabic is written right to left [14]. Table 1 shows the Arabic alphabet.

Table 1 - Arabic alphabet.

1	ا
2	ب
3	ت
4	ث
5	ج
6	ح
7	خ
8	د
9	ذ
10	ر
11	ز
12	س
13	ش
1	ص
15	ض
16	ط
17	ظ
18	ع
19	غ
20	ف
21	ق
22	ك
23	ل
24	م
25	ن
26	ه
27	و
28	ي

Arabic language has two genders (feminine and masculine), three numbers (singular, dual and plural) and three grammatical cases (nominative, accusative and genitive). Nomination of a noun is nominative, accusative one- subject of a verb and genitive one- subject of a preposition. Words can be broken down into three large units of speech comprising of nouns (including adjectives and adverbs), verbs and particles. The morphological structure of all verbs and some nouns is made out of a system of roots. The construction of words is based on the already existing patterns called affixes. These affixes are added to the word to reveal the number, gender and tense of the word. The Arabic language is a challenging language because of several reasons [15]:

- Sequence of sentences for instance, "التعليم يحتاج الى اصلاح" might be rephrased as "يحتاج التعليم الى اصلاح," as both convey the same idea. In the Arabic language, there exists a substantial quantity of free orders.

- The Arabic language exhibits complexity with the expression (يكون اعلم من السائل اعلى المسؤول ان). In light of the aforementioned obstacles, the Arabic language requires a series of preparation methods to facilitate manipulation [1].

In our research, we attempt to address these issues by identifying the optimal method to eliminate the intricacies of order and context.

2. Related Works

Most of the related works were trying to create models to predict next words, few of these works were helpful, this section will focus on the related works that used deep learning, n-gram or hybrid methods to predict next word:

2.1. Deep learning

Some of the related works that based on deep learning algorithms like CNN, RNN, LSTM, or BILSTM to predict the next word are:

F. Lahrache and S. Djebrit [16] applied the next word prediction problem (three previous words to predict the next word) to RNN and Temporal Convolutional Networks (TCN) and they used three databases (Coursera Swiftkey, Nietzsche Writings: Volume1 by Friedrich Nietzsche and news category of nltk library brown corpus). The RNN model was able to achieve the accuracy of 71.51 and TCN model with the third database was able to achieve the accuracy of 65.20.

J. YANG et al. [17] suggested a multi-window convolution and residual connection with a model of minimum gated unit network on next word prediction of natural language. Local features Local features are then identified based on the first local features that include convolution kernels of different sizes that bear specific granularity in word sequences. The obtained features are then inputted into the smallest gated unit network which is linked by its residual. The prediction is eventually yielded in the SoftMax layer. In addition to the fact that the residual connection process of the proposed model within minimal gated unit network is effective in addressing the issues of the gradient becoming vanishing and network degradation, it also effectively learns long-term relationships between word sequences to predict the subsequent word in an appropriate manner. One can mention that the experimental results on Penn Treebank and WikiText-2 databases indicate that the suggested model possesses certain strong points in the next word prediction task. The next word predicting model proposed by Sourabh Ambulgekar et al. [5] predicts a letter at a time to produce a word and they understand 40 letters and version 10 words in advance with help of the RNN neural organization which would be implemented with the help of Tensorflow, to achieve the accuracy of about 56% in 5 epochs.

In a publication by Afika Rianti et al. [18], the authors used a model with 200 epochs that are based on LSTM to forecast the following word. The author of the research adopted the use of web scraping to retrieve the data set. There are 180 destinations in nine regions in Indonesia. The libraries used by the researchers were TensorFlow, Keras, NumPy, and Matplotlib, whereas the coding tool was Google Colab. The resultant value is 8ms per step, 55 percent loss and 75 percent accuracy, which means that it is effective enough to predict the next phrases.

Milind Soam and Sanjeev Thakur [19] performed a comparative study between different deep learning techniques, and found satisfactory result in BiLSTM and LSTM, and found BiLSTM model preformed better than LSTM as BiLSTM introduced to solve the drawbacks that occured in LSTM model, and BiLSTM produced highest accuracy as well as it had least loss.

2.2. Statistical methods

A statistical model is the type of model where probability distributions on word sequences are given, namely a category of statistical language modeling methods called N-gram, which is a popular technique. When a sequence of N-1 is fed into an n-gram model, it predicts the most likely words that come after a sequence. Examples of similar papers which used this method include:

Ashfaq Ahmed et al. [20] developed an Urdu text predictor utilizing English language keyboards on PCs, tablets, or mobile devices to map Urdu characters. They employed unigrams, bigrams, and trigrams to forecast the subsequent word based on a set of prior words. This model focused on ascertaining the probability distribution of word sequences by tallying the frequency of their occurrence in a text corpus and subsequently evaluating the probabilities. The experiments indicated that the bigram model surpassed the unigram model, while the trigram model exceeded the bigram model. Hozan K. Hamarashid et al. [4] concentrated on the Kurdish language (Sorani and Kurmanji) in the context of next word prediction and developed a Kurdish corpus. The authors employed an N-gram model for next-word prediction to minimize typing duration in the Kurdish language. The application is developed using R programming and RStudio. This model exhibits an accuracy of 96.3%.

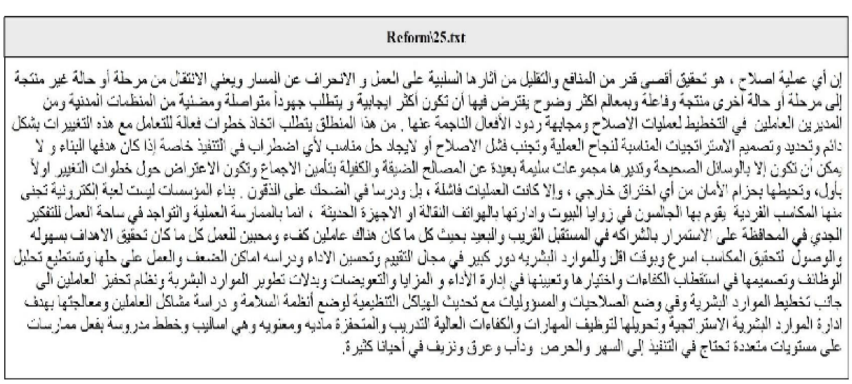
2.3. Hybrid methodologies

Several pertinent studies employ a combination of several methodologies to improve performance or augment accuracy:

Omor Faruk Rakib et al. suggested a process that would be applicable when predicting next most acceptable and suitable word in Bangali language and suggest the sentence that would be used in the prediction of the word. The given strategy trains an n-gram dataset on a Recurrent Neural Network (RNN) with Gated Recurrent Unit (GRU) to generate language models that can generate word(s) given the input sequence being fed to it. The authors employed corpus dataset to conduct the trials and their findings revealed an average accuracy of the 5-gram model, 99.70 percent, 4-gram model, 99.24 percent, tri-gram model, 78.15 percent and 32.17 percent of the bi-gram model and uni-gram model respectively. Demeke Endalie et al. [21] recommend a Bidirectional Long Short Term Gated Recurrent Unit (BLST-GRU) network algorithm of next word prediction in the Amharic language. The authors tested the proposed network methodology on 63,300 Amharic sentences with the accuracy of 78.6. They have also contrasted this method to LSTM, GRU and BLSTM and the results of the experiment showed that the developed network produced positive results.

3. Dataset

Web crawler tools were used to extract the data of numerous websites where four versions of corpses were made (V1, V2, V3, and V4) as illustrated in Fig .1 below.


Reform\25.txt

إن أي عملية اصلاح ، هو تحقيق أقصى قدر من المنافع والتقليل من آثارها السلبية على العمل و الانحراف عن المسار ويعني الانتقال من مرحلة أو حالة غير منتجة
إلى مرحلة أو حالة أخرى منتجة وفاعلة وبمعالم اكثر وضوح يفترض فيها أن تكون أكثر ايجابية و يتطلب جهوداً متواصلة ومضنية من المنظمات المدنية ومن
المديرين العاملين في التخطيط لعمليات الاصلاح ومجابهة ردود الأفعال الناجمة عنها . من هذا المنطلق يتطلب اتخاذ خطوات فعالة للتعامل مع هذه التغييرات بشكل
دائم وتحديد وتصميم الاستراتيجيات المناسبة لنجاح العملية وتجنب فشل الاصلاح أو لايجاد حل مناسب لأي اضطراب في التنفيذ خاصة إذا كان هدفها البناء و لا
يمكن أن تكون إلا بالوسائل الصحيحة وتديرها مجموعات سليمة بعيدة عن المصالح الضيقة والكفيلة بتأمين الاجماع وتكون الاعتراض حول خطوات التغيير اولاً
بأول، وتحيطها بحزام الأمان من أي اختراق خارجي ، وإلا كانت العمليات فاشلة ، بل ودرساً في الضحك على الذقون . بناء المؤسسات ليست لعبة إلكترونية تجنى
منها المكاسب الفردية يقوم بها الجالسون في زوايا البيوت وادارتها بالهواتف النقالة او الاجهزة الحديثة ، انما بالممارسة العملية والتواجد في ساحة العمل للتفكير
الجدي في المحافظة على الاستمرار بالشراكه في المستقبل القريب والبعيد بحيث كل ما كان هناك عاملين كفء ومحبين للعمل كل ما كان تحقيق الاهداف بسهوله
والوصول لتحقيق المكاسب اسرع وبوقت اقل وللموارد البشريه دور كبير في مجال التقييم وتحسين الاداء ودراسه اماكن الضعف والعمل على حلها وتستطيع تحليل
الوظائف وتصميمها في استقطاب الكفاءات واختيارها وتعيينها في إدارة الأداء و المزايا والتعويضات وبدلات تطوير الموارد البشرية ونظام تحفيز العاملين الى
جانب تخطيط الموارد البشرية وفي وضع الصلاحيات والمسؤوليات مع تحديث الهياكل التنظيمية لوضع أنظمة السلامة و دراسة مشاكل العاملين ومعالجتها بهدف
ادارة الموارد البشرية الاستراتيجية وتحويلها لتوظيف المهارات والكفاءات العالية التدريب والمتحفزة ماديه ومعنويه وهي اساليب وخطط مدروسة بفعل ممارسات
على مستويات متعددة تحتاج في التنفيذ إلى السهر والحرص وداب وعرق ونزيف في أحيانا كثيرة.

Fig. 1 - Snapshot from dataset [22].

The rationale of selecting this dataset is to be aware of what each preprocessing step has on the following step prediction of the word. These are four versions which constitute raw data V1, preprocessing V2, root stemming V3 and light stemming V4.

4. The Proposed System

This paper builds next word prediction model of the Arabic language to enhance the writing of various Arabic based applications. We develop model using the LSTM neural network; the LSTM is generally regarded as the foundation of most next word prediction in a variety of languages. We use Several preprocessing treatments on data to find out better results, and as shown below:

1. Sentence segmentation:
   - Split text into sentences using Arabic punctuation (، ؟. !).
   - Discard extremely long sentences.
2. Tokenization with Context Preservation.
   - Use Arabic-aware tokenization.
   - Avoid aggressive splitting that breaks semantic flow.
3. Light Stemming (Optional, Not Aggressive)
   - Remove only common prefixes/suffixes.
   - Avoid root-based stemming.
4. Stop Words Handling (Keep Them)
   - Do not remove stop words.
   - Keep function words (في، على، من، إلى).
5. Noise Removal
   - Remove URLs, hashtags, emojis, foreign symbols.
   - • Normalize numbers (optional).
   - Prevents irrelevant tokens from disturbing sequence patterns. The proposed system of next word prediction for Arabic language shown in Fig. 2.

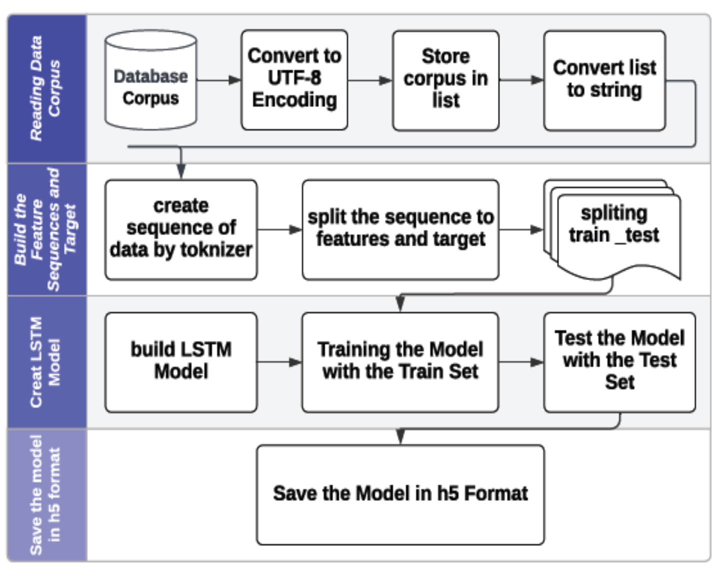


Fig. 2 - Proposed system of next word prediction for Arabic language.

4.1. Reading corpus

The text data files are uploaded to the drive and read in Google Collab after that converting data to list then convert list to string.

4.2. Building the feature sequences

The data in each version is organized as two arrays, one two dimensions for the features (three column) and other one dimensions for the target, each three words as features construct the input vector and the fourth word is the target (next word), the details of each data version of shown in Table 2.

Table 2 - An example of a table.

Corpus version	No. of words	vocab_size	No. of instances
V1	391343	17244	63275
V2	281942	12689	39967
V3	148242	3255	34714
V4	206421	7571	36027

4.3. Create LSTM model

Fig. 3 shows the model architecture. Tf.keras.utils.plot model was used to visualize the model.

In order to show the name of the layer, one just needs to set the show_layer_names value to True. In order to download the model and give it a name, use the to file option and then give the file name. we employed this straightforward model to minimize runtime. Fig. 4 presents a summary of the model.

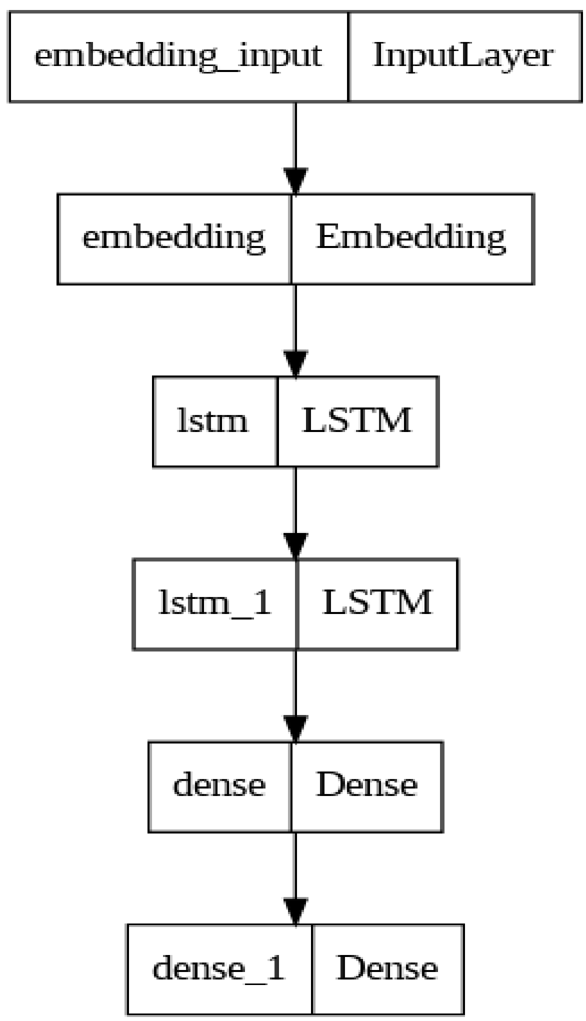


Fig. 3 - Model architecture.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 3, 10)             172440

 lstm (LSTM)                 (None, 3, 200)            168800

 lstm_1 (LSTM)               (None, 200)               320800

 dense (Dense)               (None, 200)               40200

 dense_1 (Dense)             (None, 17244)             3466044

=================================================================
Total params: 4,168,284
Trainable params: 4,168,284
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4 - Model summary.

Training parameters are shown in Table 3:

Table 3 - No. of instances for training, validation and testing of each version.

Parameter	Learning rate	Epoch	Batch size	Monitor
Value	0.01	50	128	loss

5. Results and discussion

To predict the next word in Arabic language, word sentences have been prepared as input to the LSTM model. The training was done without a validation set and with a validation set as follows:

5.1. Training results without validation

The splitting data for each version to training 80% and testing 20% of instances as shown in Table 4.

Table 4 - No. of instances for training, validation and testing of each version.

Corpus version	Training set	Testing set
V1	50620	12655
V2	31973	7994
V3	27771	6943
V4	28821	7206

In this work we depend on accuracy and loss graph in order to show our experimental results. In Fig 5 the graph is plotted for accuracy vs epochs whereas the graph in Fig. 6 is plotted for loss vs epoch. All without validation set, and as shown in bellow.

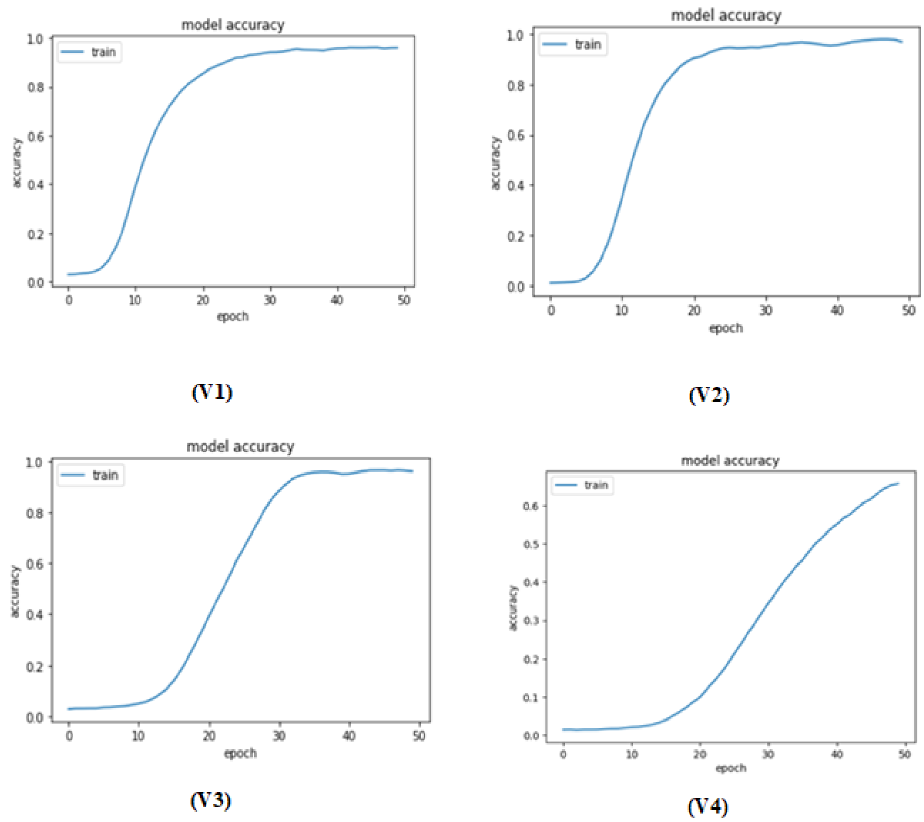


Fig. 5 - Model accuracy of training without validation set.

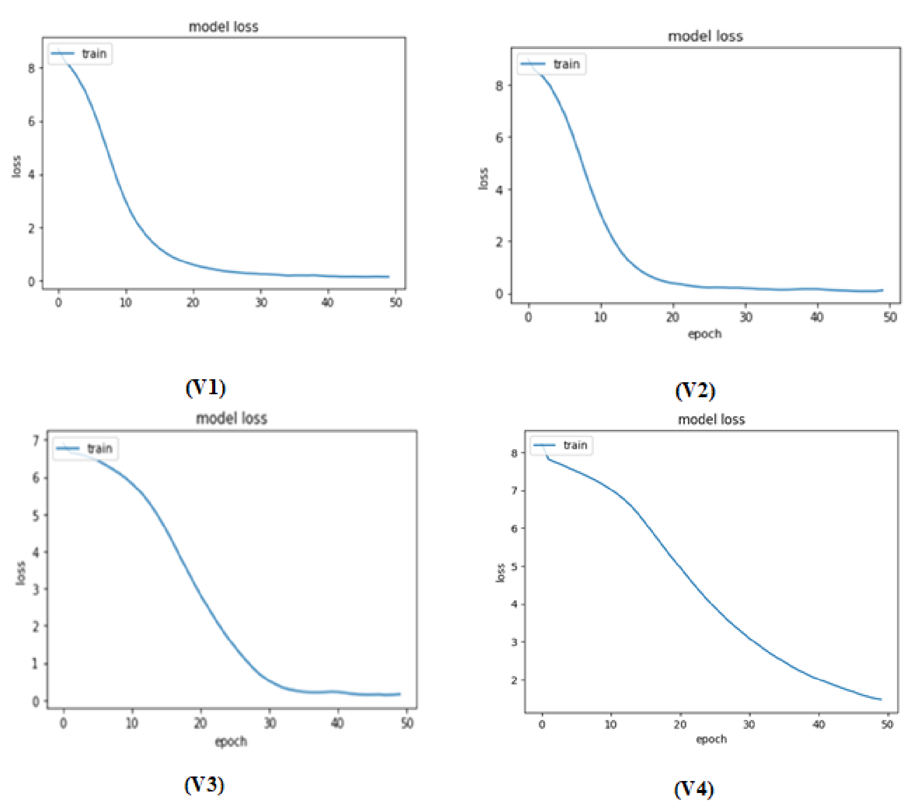


Fig. 6 - Model loss of training without validation set.

Table 5 below shows the training and testing details.

Table 5 - The training and testing details.

Corpus version	Training Accuracy	Training Loss	Test Accuracy	Testing Loss
V1	92.94	0.6931	0.16	39.39
V2	**97.49**	**0.5155**	**0.15**	**46.68**
V3	73.39	0.4318	0.093	17.821
V4	75.82	1.4928	0.136	33.49

5.2. Training with validation

The splitting data for each version to training 60%, validation 20% and testing 20% of instances as shown in Table 6.

Table 6 - No. of instances for training, validation and testing of each version.

Corpus version	Training set	Validation set	Testing set
V1	37965	12655	12655
V2	23979	7994	7994
V3	20828	6943	6943
V4	21615	7206	7206

In Fig 7 the graph is plotted for model accuracy of training whereas the graph in Fig. 8 is plotted for model loss of training. All with validation set , and as shown in bellow.

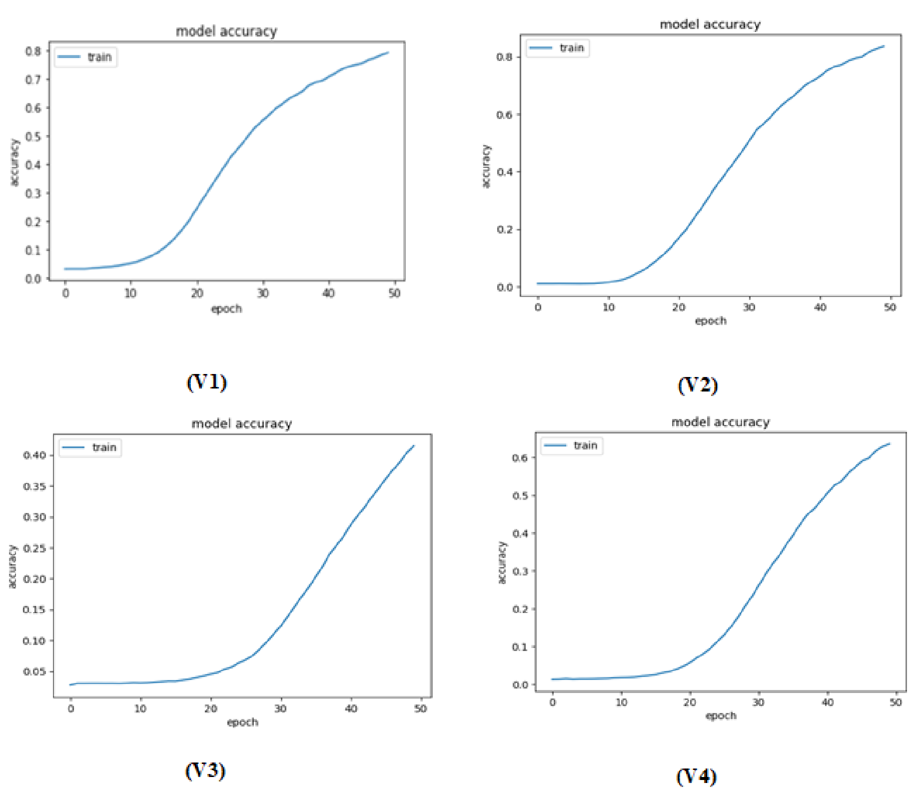


Fig. 7 - Accuracy of training with validation set.

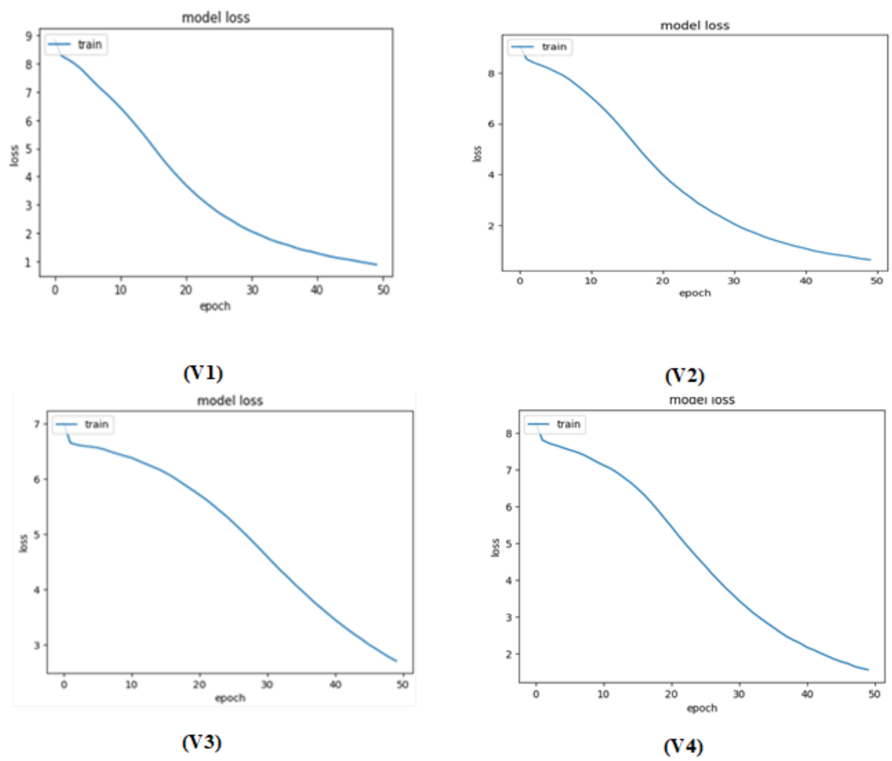


Fig. 8 - Loss of training with validation set.

Table 7 shows the training and testing details with validation:

Table 7 - The training and testing details with validation.

Corpus version	Training Accuracy	Training Loss	Validation loss	Validation accuracy	Test Accuracy	Testing Loss
V1	80.22	1.0181	39.8796	0.1194	0.119	39.472
V2	**83.65**	**0.6526**	**49.7140**	**0.1245**	**0.126**	**48.939**
V3	41.47	0.7123	18.0516	0.0774	0.073	18.103
V4	63.50	1.5693	33.5616	0.1032	0.1142	33.424

We observe in Table 7 that the accuracy of the training set is greater than test set and validation set, this issue is not caused by the absence of training data, but because of the variety of vocabulary of the language as we described it previously in section 1.1 which is regarded as the big challenge in Arabic language.

6. Conclusion

Next word prediction is one of the areas that are included in the umbrella of natural language processing because it entails mining the text. To make the prediction using the Arabic data. We have used the LSTM model in four variations of preprocessing in this study. The result proved the most effective version because Arabic language is more complex than other languages and has multiple uses of vocabulary, the precision of the test is rather low. Due to the fact that the training is accurate, the model requires periodic retraining while it is being used in order to incorporate the newly acquired vocabulary. There are more ideas expected to be implemented in the future, such as:

- Improving prediction accuracy by considering the rich morphological structure of Arabic words, including prefixes, suffixes, and root patterns.
- Supporting Arabic dialect variations in addition to modern standard Arabic to make predictions more practical for real-world usage.

- Reducing prediction errors caused by data sparsity by using data augmentation or transfer learning techniques.
- Improving robustness when users mix Arabic with English words or numbers during typing.
- Evaluating the system based on user experience, such as typing, speed and correction rate, rather than relying only on statistical accuracy measures.

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