إطار عام يعتمد على التعلم العميق للترجمة الرقمية من اللغة العربية إلى اللغة الإجليزية

A General framework based on deep learning for digital translation from Arabic to English

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ABSTRACT

This paper proposes a way to develop a machine translation system based on deep learning for the translation of Arabic texts into English. This system is for translating texts in the computer field, The proposed system contains six main stages and the system will be included in a database containing a bilingual dictionary (Arabic-English) containing terms in the field of Computer-based, the system was evaluated by human experts in addition to using the bleu scale, The system has been evaluated by comparing between manual and automatic translation and some measurements are used especially bleu measure. The manual translation is done by two human experts to check the translation quality in terms of the general form, content meaning, coherence of the phrases, and completeness of the. The final results proved that the proposed method achieved higher performance than other systems.

Key Words: Machine translation, NMT systems, Arabic machine translation, Natural Language Processing.

1. INTRODICTION

In recent ten years, Artificial Intelligence (AI) techniques have been booming globally, due to the accumulation of big data, innovation of algorithms, and improvement of the computer processing capacity **(Xin, Y., Man, W., & Yi, Z. 2021, p1-10)**. AI has significantly impacted a number of fields including, among others, image analysis or natural language processing, and is spreading out to different areas beyond informatics including the life and biomedical sciences **(Carolina, A. 2021. p 1-2)**

Natural language processing (NLP) is an important component in a wide range of software applications that we use in our daily lives **(Vajjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77)** . Natural language processing with neural networks has grown in importance over the last few years. They provide state-of-the-art models for tasks like coreference resolution, language modeling, and machine translation **(Boucher, P. 2020 .p1)** .

Machine translation is one of the most important automated systems that contribute significantly to the transfer of science and knowledge between the languages of the world. It also facilitates human communication despite differences in tongues and beliefs (عبادوا، فضيلة.، و خديش، صالح. ٢٠١٩ . ص ص ، ٢٩٣-٣٣٠ .). Machine translation is the task of converting a piece of text from one language to another. Tools like Google Translate are common applications of this task, Figure 1 shows a depiction of these tasks based on their relative difficulty in terms of developing comprehensive solutions (Vjjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77).
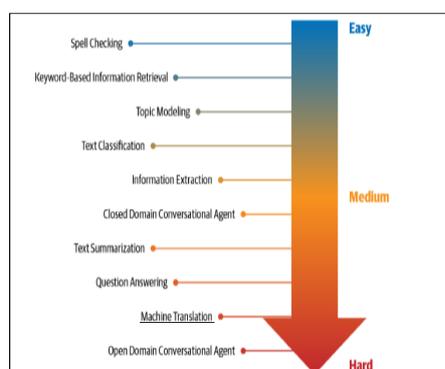

Fig.1. NLP tasks organized according to their relative difficulty
[**Vjjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77**).]

Machine translation (MT) —translating text from one language to another automatically—is one of the original problems of NLP research **(Vajjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77)** As the demand for translation has increased tremendously, MT is now widely used around the world Human translators cannot cope with the large amount of the materials that are needed to be translated in every field. They, thus, can use MT to help them meet such demands, as MT systems can save them time and effort **(Sabtan, Y. 2020. p 184-197)**. Consequently, research in this field is constantly growing and new MT paradigms are emerging **(Trigueros, I. ,2021, P595)**. Oral translation is the translation of uttered words unlike written translation, which deals with written texts [(دباب، نسرين.، و شكيمة، أسماء. ٢٠١٩. ، ص١)]. In this paper, we will specialize in studying the written translation.

MT systems are divided into [**(Sabtan, Y. 2020. p 184-197)**, **(Trigueros, I. ,2021, P595)**Rule-Based Machine Translation Systems (RBMT).

- The corpus-based Machine Translation Systems.
- Hybrid Machine Translation Systems.
- Neural Machine Translation Systems (NMT).

Figure 2 shows the Classification of machine translation systems:
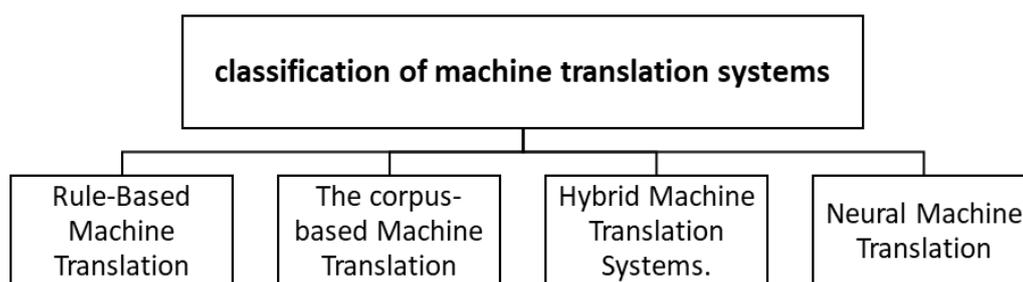

Fig. 2. Classification of machine translation systems

In recent years, natural language processing (NLP) has got great development with deep learning techniques. In the sub-field of machine translation, a new approach named Neural Machine Translation (NMT) has emerged and got massive attention from both academia and industry **(yang, S., Wang, Y., & Chu, X. ,2020, PP2,4)**. As NMT is currently dominating the

paradigms of machine translation (**Trigueros, I. ,2021, P595**), the inspiration for neural machine translation comes from two aspects: the success of Deep Learning in other NLP tasks and the unresolved problems in the development of MT itself (**yang, S., Wang, Y., & Chu, X. ,2020, PP2,4**).This promising approach is now, the state of the art in MT as it has become the preferred paradigm in the field (**Sabtan, Y. 2020. p 184-197**). Google Translate is a popular example of NMT (**Vajjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77**) , (**Sabtan, Y. 2020. p 184-197**) .

2. RELATED WORK

Arabic machine translation has an important role in most NLP tasks, many machine translation systems that support Arabic exist already, however, the quality of the translation needs to be improved [*https://ieeexplore.ieee.org/abstract/document/9079094*].   the current state of Arabic MT systems has not reached the quality achieved for some other languages. Thus, much research work is still needed to improve it

 (https://www.sciencedirect.com/science/article/abs/pii/S1574013720304056)

This section discusses some of these NMT systems and reviews some systems of machine translation of Arabic texts:

S. Khaled et al. (2010): Built a translation system using a Rule-based transfer machine translation technique to translate expert systems in the agriculture domain from English to Arabic and vice versa. This translation process includes translating the knowledge base, in particular, prompts, responses, explanation text, and advice. Those expert systems are built in CLAES] (**Khaled, S., Hendam, A., & Rafea, A. 2010., 281-290**).

F. Mallek et al. (2018): The implementation of a phrase-based statistical machine translation system for tweets, from Arabic, into English called (AlMoFseH). for both the source and target languages. Special attention is given to the pre-processing of Arabic tweets, an out-of-domain corpus was incorporated for training a translation model, and an adaptation strategy of a bigger language model for English tweets was used in the training step.

evaluations confirm that pre-processing tweets of the source and target languages improves the performance of the statistical machine translation system. In addition, using in-domain data for the language model and the tuning set, showed a better performance of the statistical machine translation system from Arabic to English tweets. Also, carried out the spelling and orthographic mistakes in tweets, by normalizing the stretched words, the transliterated expression, etc. These pre-processing steps were very helpful and ameliorated the bleu score, which reached (10.98) **(Hamada, S., & Marzouk, R. 2018., 121-138)**

R. Ehab, et al. (2019): A hybrid machine translation system using Example based machine translation technique and Translation memory was introduced to translate English medical terms to Arabic medical terms in comparison with using Google translate only to translate, Example-based machine translation system using matching stage only and finally with a hybrid system using Example based machine translation technique and Google Translate. The system that used Example based machine translation technique with a Translation memory achieved the highest score in comparison with the other three experiments and because the Translation memory that was used stores the translation of each medical term when using it to translate the unmatched portions of the input sentence (Si) that were added to the translated text (St) of the closest sentence (Se) from the database in the recombination stage translation of the unmatched portions to the right Arabic medical term will be ensured. For the first dataset, the proposed system achieved (77.17 %) **(Ehab, R., Gadallah, M., & Amer, E. 2019, 195-203**)

N. Dababa, A. shakima. (2019): In this research, a system was proposed, which is a semantic coding system that helps in Obtaining a satisfactory translation, to solve the problem of translating meaning, (work the duality between the machine and the author) for that it helps him in deciphering the three types of ambiguity: lexical, cultural, and synthetic if it is found in the text.

the text goes through steps in different ways to be ready for translation, starting with processing the text and then deciphering the lexical ambiguity. the result that the machine is still unable to reach perfection without human intervention due to the difficulties and obstacles it may face. On the contrary, human intervention is necessary, so this system relies upon on double work between the machine and the human. To solve three types of ambiguity: lexical, cultural, and syntactic [(دباب، نسرين.، و شكيمة، أسماء. ٢٠١٩. ، ص١)].

N. Bensalah et al. (2020): A hybrid machine translation system using CNN-RNN attention-based neural network is proposed. During training, the Adam optimizer algorithm is used, and then, a popular regularization technique named dropout is applied in order to prevent some learning problems such as overfitting. The experiments were conducted over our own Arabic-English corpus. the database was divided randomly into a training set, a validation set, and a testing set 20,800 sentences for both Arabic and English languages were used for training, and 600 To build our corpora, results show that the proposed method is capable of providing satisfactory performance for Arabic MT (bleu score =0.57) . **(Nouhaila, B., Habib, A., Abdellah, A., & Abdelhamid, I. 2021)**

3. METHODS AND MATERIAL

This paper focuses on NMT systems, NMT is developed with deep learning techniques; it's kind of MT attempts to build and train a single, large neural network that reads a sentence and outputs a correct translation. These systems are based on neural networks to create translations thanks to a recurrent neural architecture, based on the encoder-decoder model in which the encoder reads and encodes the source sentence into a fixed-length vector while the decoder produces a translation output from the encoded vector Consequently, this architecture implies a simplification regarding previous paradigms, given that they use less components and processing steps **(Trigueros, I. ,2021, P595)**

We think that attention to creating a specialized dictionary and Arabic text pre-processing stage; and addition to choosing a recurrent neural network (RNN), will effectively affect the quality of translation. The proposed system

consists of several steps beginning with entering the Arabic document to be automatically summarized into the proposed system. The Python language will be used to write the code for the proposed system as well as a set of other libraries. According to the natural language processing pipeline shown in Figure 3 **(Vajjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77)**, a digital translation model based on deep learning techniques shown in Figure 4 has been proposed.
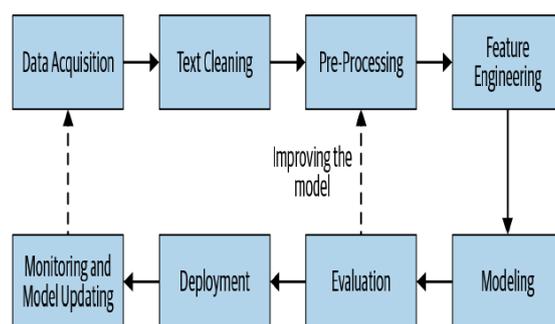

Fig. 3. Generic NLP pipeline

[**Vjjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77)**

The proposed system has five main stages as follows:

1.   Data acquisition & text cleaning
2.   Pre-process Arabic text
3.   Tokenize Arabic text
4.   Modeling (Train and test a model)
5.   Evaluation & Deployment

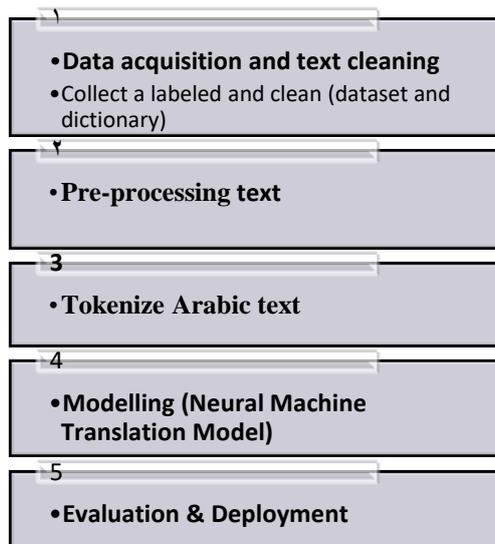   The basic process flow of generic NMT system is shown in Figure 4.

Fig. 4. Generic NMT proposed system

3.1 First stage: Data acquisition

The proposed system needs a dataset, this dataset contains two language translation pairs (Arabic -English), we use a public dataset from Anki, addition create a special dataset on the computer field; Create and prepare the dataset (dictionary Arabic-English), The Excel program will be used to create a dataset (English-Arabic dictionary) specialized in the computer field

There are some the steps we need to take to prepare the data:

1. Clean the sentences by removing special characters.
2. Create a word index and reverse word index.
3. Pad each sentence to a maximum length.

This stage is done through the following Algorithm:

Algorithm1
Input: Dataset
Operation:
Clean the sentences (remove special characters)
Create a word index (dictionaries mapping)
Pad each sentence to a maximum length
Output: one array contains all pairs sentences (Arabic -English)

3.2 Second stage: Pre-processing text

The pre-processing stage aims to obtain a structured representation of the original text, and this phase includes the following:

- Sentence Boundary Identification: in Arabic, the limits of the sentence are determined by using a set of punctuation marks at the end of the sentence such as: (، ، ؛ ، .).
- Remove repeated sentences.
- Remove parentheses and quotation marks: The parentheses are removed such as ("," ( ), [ ],}{).
- Normalization Alef by replacing (ٱ ، ٱ ، آ ، إ ، أ) to (ا), Normalization Yaa by replacing (ي) to (ى), and Normalization Tah by replacing (ة) to (ه), and the deletion of the diacritical marks (ْ ، ّ ، ِ ، ٌ ، ٔ ، ٍ ، َ ، ً).
- Remove punctuation marks: punctuation marks such as (? ، :).
- Remove spaces: Spaces between words are removed if two or more spaces exist.

    Now that the text data has been cleaned, we can save the list of phrase pairs to an Array ready for use.

    This stage is done through the following Algorithm:

Algorithm2
Input: all text

Operation:
    Split text using (. , ؛ , : , ،)
    Remove repeated sentences.
    Removing Brackets ([ ] , ( ) , «» , { }, " ")
    Normalization aleph by replacing (ٱ ، ٱ ، آ ، إ ، أ) to (ا) , Normalization yaa by replacing (ي) to (ى) , and Normalization ta by replacing (ة) to (ه)
    Removing all diacritics (ْ ، ّ ، ِ ، ٌ ، ٔ ، ٍ ، َ ، ً)
    Removing all punctuation from all sentences
    Removing all spaces between words from all sentences.

Output: one array contains all sentences.

3.3 Third stage: Tokenize text

In this section, we can use the Keras Tokenize class to map words to integers, as needed for modeling. We will use separate tokenizer for the Arabic sequences and the English sequences. The function below-named "create_tokenizer()" will train a tokenizer on a list of phrases.

The following algorithm shows the stage of Tokenize stage:

Algorithm3
Input: one array all sentences embedding.
Operation:
def create_tokenizer(lines)
tokenizer = Tokenizer()
tokenizer.fit_on_texts(lines)
return tokenizer.
Output: one array all sentences tokenizer.

3.4 Fourth stage: NMT Translation Model

In this paper, we propose a neural network architecture or "neural sequence-to-sequence models" that learns to encode a sequence into a fixed-length vector representation and to decode a given fixed-length vector representation back into a variable-length sequence. We used sequence-to-sequence models is many reasons:

- RNNs are powerful and work very well for solving a variety of NLP tasks, such as text classification, named entity recognition, machine translation, etc... **(Vajjala, S., Majumder, B., Gupta, A., & Surana, H. ,2020 ,p48,77)**

- Machine translation is a widely recognized and useful instance of sequence-to-sequence models and allows us to use many intuitive examples demonstrating the difficulties encountered when trying to tackle these problems **(Neubig, G. 2017., P2)**.

The following diagrams show an overview of the model. In both, the encoder is on the left, and the decoder is on the right. At each time step the decoder's output is combined with the encoder's output, to predict the next word, Figure 5 shows the modeling stage:
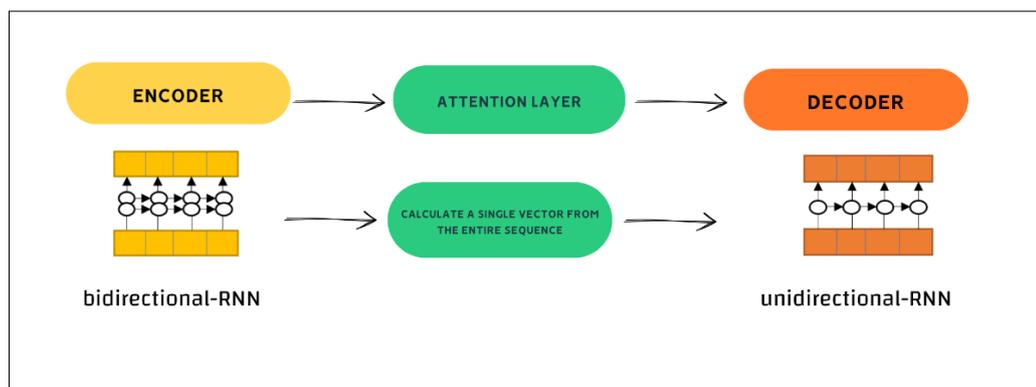
Fig .5. Modeling (Neural sequence-to-sequence Models for NMT)

3.4.1 THE ENCODER

The goal of the encoder is to process the context sequence into a sequence of vectors that are useful for the decoder as it attempts to predict the next output for each time step. Since the context sequence is constant, there is no restriction on how information can flow in the encoder, so use a bidirectional-RNN to do the processing, Figure 6 shows the bidirectional-RNN:
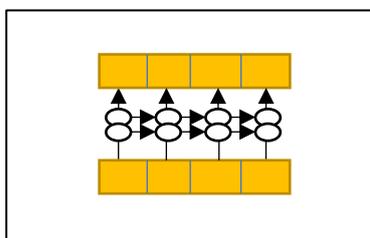

Fig.6. The bidirectional-RNN

The following algorithm shows the stage of THE ENCODER.

Algorithm4
Input: one array contains all sentences.
Operation:
Takes a list of token IDs (from context_text_processor).
Looks up an embedding vector for each token (Using a layers. Embedding by tensorflow + keras)
Processes the embeddings into a new sequence (Using a bidirectional layers.GRU).
Returns the processed sequence.
Output: one array all sentences embedding.

3.4.2 THE ATTENTION LAYER

An attentional mechanism has lately been used to improve neural machine translation (NMT) by selectively focusing on parts of the source sentence during translation **(Luong, M., Pham, H., & Manning, C. 2015, P1)**, and the objective is to provide additional word alignment information in translating the long sentence **(yang, S., Wang, Y., & Chu, X. ,2020, PP2,4)**

The attention layer lets the decoder access the information extracted by the encoder. It computes a vector from the entire context sequence and adds that to the decoder's output.

The simplest way you could calculate a single vector from the entire sequence would be to take the average across the sequence (layers.GlobalAveragePooling1D), An attention layer is calculating a weighted average across the context sequence. Where the weights are calculated from the combination of context and "query" vectors, Figure 7 shows the attention layer:
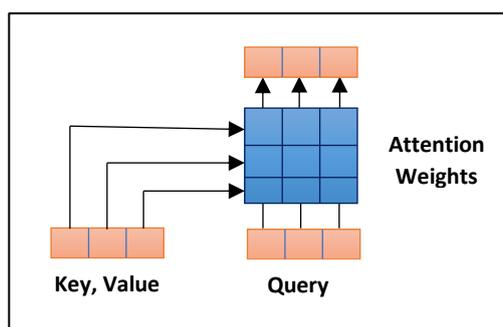

Fig .7. The attention layer is similar

The following algorithm shows the stage of the Attention layer.

Algorithm5
Input: one array of all sentences embedding.
Operation:
It looks up embeddings for each token in the target sequence.
It uses RNN to process the target sequence
It uses RNN output as the "query" to the attention layer
At each location in the output, it predicts the next token.
Output: one array of all sentences embedding.

3.4.3 THE DECODER

The decoder's job is to generate predictions for the next token at each location in the target sequence at each location in the output. When training, the model predicts the next word at each location. So, it's important that the information only flows in one direction through the model. The decoder uses a unidirectional (not bidirectional) RNN to process the target sequence, when running inference with this model it produces one word at a time, Figure 8 shows the unidirectional RNN:
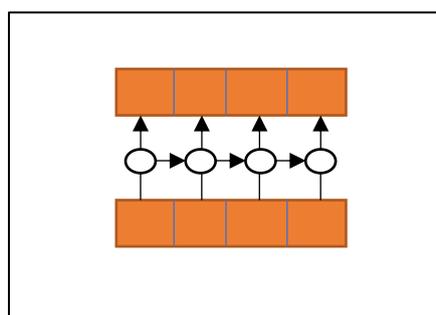

Fig .8. The unidirectional-RNN

3-5 Fourth stage: Evaluation & Deployment

This stage aims for training for translation, Algorithm fully online training (Neural sequence-to-sequence Models), The following algorithm shows the fourth stage:

Algorithm6
Input: one array of all sentences embedding (source sentences)
Operation:
procedure Online
for several epochs of training do
for each training example in the data do
Calculate gradients of the loss
Update the parameters according to this gradient
Output: one array of all sentences embedding (target sentences)

4. EXPERIMENT AND RESULTS

To evaluate the quality and efficiency of the proposed system, we can use accuracy and the bleu; additional metrics were used: Precision (P), Recall (R), and F1-Score (**Guellil, & others ,2020. p 101-128**). shows following:

$$Recall = \frac{TP}{TP+FN} \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

$$Fmeasure = \frac{2*Recall*Precision}{Recall+Precision} \qquad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

Where: TP is the number of sentence pairs in the human expert translation and system translation.

TN is the number of pairs of sentences not found in the expert translation and system translation.

FP is the number of sentences in the system translation that are not in the expert translation.

FN is the number of sentences in the expert translation that are not in the system translation.

Bleu metric is calculated by comparing the n-grams of machine-translated sentences to the n-gram of human-translated sentences. Usually, it has been observed that the bleu score decreases as the sentence length increases. This, however, might vary depending on the model used for translation
https://www.geeksforgeeks.org/nlp-bleu-score-for-evaluating-neural-machine-translation-python/

The Python Natural Language Toolkit library, or NLTK, provides an implementation of the BLEU score that you can use to evaluate your generated text against a reference, NLTK provides the "sentence_bleu()" function for evaluating a candidate sentence against one or more reference sentences .

https://machinelearningmastery.com/calculate-bleu-score-for-text-python/.

4.1 Evaluation of human experts of the proposed system in the following three levels:

We will use the fifth Likert scale to evaluate the three levels of the proposed system: the general form and content, the coherence of the phrases, completeness of the meaning, Table (1) presents the fifth Likert scale.

Table (1) The fifth Likert scale used to evaluate the three levels of the proposed system

Evaluation items	Refers to	Degree
Very poor	The translation doesn't exist, the translation cannot be considered as representing the original text	1
Poor	Either the translation is incomplete or illogical, or focuses on less important points in the original text	2
Fair	The translation can be understood but needs effort, covering some important points in the original sentence	3
Good	The translation can be easily understood and covers most of the important points that occur in the original text	4
Very Good	The translation is read as if it were written by a human, that is, it covers the idea very well about what was discussed in the original	5

4.2 General Comparison between The Proposed System and other automatic translation systems:

In order to judge the efficiency and accuracy of the proposed system in the light of previous studies, the results of the proposed system were compared with other automatic translation systems for Arabic texts. Table (2) shown the Bleu score between the proposed system and other automatic translation systems.

Table (2) the bleu score between the proposed system and SMT system

The measure	Bleu
the proposed system	55 %
A hybrid MT using CNN-RNN	57%
AlMoFseH	10.98 %

It is clear from the previous table, that the MT using CNN & RNN was the first according to the bleu score, it was 57%, while proposed system was 55%, and the STM was the last 10.98%, this refers to the ability of the proposed system to produce translations good.

5. CONCLUSION

This paper proposed digital translation system based on deep learning for the translation of Arabic texts into English. This system is for translating texts in the computer field, The proposed system contains five main stages and contains in a database containing a bilingual dictionary (Arabic-English) containing terms in the field of Computer-based, the system was evaluated by human experts, addition to using the bleu scale, The system has been evaluated by comparing between manual and automatic translation and some measurements are used especially bleu measure. The manual evaluation was by human experts to check the translation quality in terms of: the general form, content meaning, coherence of the phrases, and completeness of the final results proved that the proposed method achieved higher performance than other systems.

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إطار عام يعتمد على التعلم العميق للترجمة الرقمية من العربية إلى الإنجليزية

المُلخص:

تقترح هذه الورقة طريقة لتطوير نظام ترجمة رقمي يعتمد على التعلم العميق لترجمة النصوص العربية إلى الإنجليزية. هذا النظام مخصص لترجمة النصوص في مجال الحاسوب، يحتوي النظام المقترح على خمس مراحل رئيسية، يحتوي النظام علي قاعدتين بيانات أحدهما عامة؛ والأخرى قاعدة بيانات خاصة عبارة عن قاموس ثنائي اللغة (عربي - إنجليزي) يحتوي على مصطلحات في مجال الحاسوب، ولتقييم النظام نستعين بخبراء بشريين بالإضافة إلى استخدام مقياس بلو من خلال المقارنة بين الترجمة اليدوية والآلية؛ حيث تتم الترجمة اليدوية بواسطة خبراء بشريين، و للتحقق من جودة الترجمة من حيث الشكل العام، المعنى وتماسك العبارات ، اكتمال النص تم اقتراح استبيان يعتمد على مقياس كارتر الخماسي، وأثبتت النتائج النهائية أن الطريقة المقترحة حققت الأداء الأعلى من الأنظمة الأخرى.

ومن الجدير بالذكر أن النظام المقترح للترجمة يمكن تطبيقه في مجالات كثيرة ، مع مراعاة تغيير قاعدة البيانات بما يتوافق مع المجال، ونوصي بالإهتمام بمرحلة Pre-processing فهي تؤثر على جودة الترجمة.

الكلمات المفتاحية: الترجمة الآلية، أنظمة NMT، الترجمة الآلية العربية، معالجة اللغات الطبيعية.