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AUTOMATIC TRANSLATION OF ARABIC TEXT TO ARABIC SIGN LANGUAGE USING DEEP LEARNING

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ABSTRACT

Deaf and dumb people are an integral part of society, must be merged with it, and must be able to communicate natively in order to get involved with the various aspects of life. The language of communication between the deaf and dumb is sign language; a language that is not known by almost all those who do not suffer from the deficiency. Therefore, this research focuses on automating the translation of Arabic text into Arabic Sign Language (ArSL) in order to enable normal people to communicate with the deaf and dumb without being overburdened. This article discusses how deep Learning and Neural Machine Translation (NMT), particularly Encoder-Decoder Transformer Architecture Model, can aid this translation process.

The proposed model has been trained on a manually generated dataset of 6500 pairs of Arabic sentences and their corresponding intermediate representation of Arabic sign sentences. The produced learning model was able to translate an input Arabic sentence into an intermediate format of Sign Language with an accuracy of 72%. After generating an intermediate sentence, a video is then generated for its corresponding Sign Language. The model achieved an average BLEU score of 69% on the test data.

KEYWORDS: Arabic Sign Language, Automatic Translation, NLP, Deep Learning, Encoder-Decoder Transformer Architecture Model.

الترجمة الآلية للنص من اللغة العربية إلى لغة الإشارة العربية بإستخدام التعلم العميق

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الملخص

يعتبر الصم والبكم جزءًا لا يتجزأ من المجتمع ، ويجب دمجهم معه ، ولذا يجب أن يكونوا قادرين على التواصل بشكل طبيعى من أجل المشاركة في مختلف جوانب الحياة. لغة التواصل بين الصم والبكم هي لغة الإشارة وهى لغة لا يعرفها تقريبا كل الأشخاص الأصحاء الذين لايعانون من فقدان السمع لذلك ، يركز هذا البحث على ترجمة النص العربي إلى لغة الإشارة العربية (ArSL) من أجل تمكين الأشخاص الطبيعيين من التواصل مع الصم والبكم دون إرهاقهم.

تناقش هذه المقالة كيف يمكن أن يساعد التعلم العميق والترجمة الآلية العصبية (NMT) في عملية الترجمة هذه. وقد قمنا بإنشاء قاعدة بيانات خاصة بنا يدويًا تتكون من 6500 زوجًا من جملة عربية وتمثيلها الوسيط المقابل لجملة الإشارة العربية. كما استخدمنا خوارزميات التعلم العميق (Encoder-Decoder

(Transformer Architecture Model). وأصبح نموذج التعلم الناتج قادرًا على ترجمة جملة عربية إلى جملة وسيطة للغة الإشارة بدقة 72٪. وبعدها يتم إنشاء مقطع فيديو للغة الإشارة المقابلة من هذه الجملة الوسيطة.

الكلمات المفتاحية : لغة الإشارة العربية ، الترجمة الآلية ، التعلم العميق ، معالجة اللغات الطبيعية.

1. INTRODUCTION

Language, whether verbal, sign, or hint has a significant place among human structures and is a means for acquaintance, communication, and exchange of ideas, information, science, and cultures. Language is a means of coexistence, knowledge of feelings, and communication between individuals, universities, peoples, and institutions that need a bond and a means through which they communicate. Even people with special needs, e.g., blind and hearing-impaired people can communicate with artificially developed languages, such as Braille sign languages [1]. The sign language of deaf and dumb people uses hand gestures, facial expressions, and body movements as base vocabulary.

Sign language translation is not easy; hence, human translators are scarce. Therefore, the interest in automated machine translation comes first attention, accordingly, machine translation systems have been developed to translate into sign language and vice versa [2].

In this research, a model was developed for machine translation from Arabic-to-Arabic Sign Language to solve the problem of communication between hearings impaired and normal people. This research created a special dataset of several Arabic sentences and their translations into an intermediate transformation of Sign Language. This dataset was used by the Encoder-Decoder Transformer Architecture of the Recurrent Neural Network (RNN) deep learning in order to reach a machine-learning model. The produced learning model was able to translate an input Arabic sentence into an intermediate format of Sign Language with an accuracy of 72%. The intermediate transformation was then passed to another level of interpretation to compose the gesture language that is played by an Avatar to communicate the sentence to the deaf. This way, written or spoken Arabic sentences are translated and visually animated in the standard Arabic Sign Language.

Section 2 of this article reviews many of the related research works, while Section 3 sheds light on Arabic Sign Language and its relationship to the Arabic language explaining the rule of translation and the problems entailed. The Proposed Framework and an overview of the developed solution are presented in Section 4. Section 5 presents and discusses the experimental implementation and its results, while Section 6 concludes and suggests a few future research directions.

2. RELATED WORK

In the past years, language translation has been an interesting research topic that has attracted several researchers worldwide. Sign language had a special interest due to its special nature of being visual rather than spoken, besides several other entailed difficulties, hence, grabbed the attention of very few researchers having the motive of facilitating communication between deaf people and natural persons. Arabic sign language has a unique distinction between languages due to a large number of deaf people, especially in the Arab world, and the difficulty of the Arabic language, e.g., a machine translation system between Arabic and sign language based on rules and differences between Arabic and sign language was developed, and This system is developed to perform morphological, syntactic, and semantic analysis of an Arabic sentence to translate it into a sentence with the grammar and structure of ArSL. A system of gestures to represent sign language was developed, consisting of 600 sentences in the health domain [3].

While there was used a feed forward-back propagation Artificial Neural Network algorithm to implement a machine translation system from Arabic-to-Arabic Sign Language. They applied three steps: analysis, transfer, and generation. The first step is morphological-syntactic analysis, which extracts the morphological characteristics for each word of the sentence. Since neural networks accept only numbers as input data, the second step allows the sentence to be encoded with the morphological properties of each word and provides a context vector representing the sentence to be translated. A target vector is generated using a feed forward neural network with back propagation from the context vector and based on the produced objects of the learning performed. The next step is decoding of the vector produced in a sentence in Arabic Sign Language [4].

Interest was shown in learning sign language for deaf children. A system was implemented that works on 3 models, namely, sign-to-text, text-to-sign, and student scoring. This system can work in two modes, teacher-based mode, and automatic mode. The system provides the child with the text, physical meaning, and ArSL signs. It also can provide an assessment tool to measure the child's capabilities and learning rate. It can also help normal family members to learn ArSL to be able to communicate better with hearing impair children [5].

A mobile application was developed that can be used to translate from Arabic speech to Arabic sign language, using 588 signs (pattern-word-letter) saved in a database, the pattern is a sentence that contains two or more words and has only one sign in Arabic sign language. Google API is used to recognize the input voice and convert it to text, then preprocess text by Microsoft Arabic Toolkit Service (ATKS) on the cloud, then used Avatar in the output video to display the sign [6].

While a translation system from Arabic text to Arabic sign language was developed. The system parses the input sentence to identify each part of the sentence such as noun, verb, adjective, number, or a word to be ignored. The words in the sentence are extracted individually and extra unnecessary parts of these words are stripped then, word processing: If the word has no meaning after being stripped, it is deleted. If the word is meaningful, this stage will check if the word is in the system's database. If it exists in the database, it will be forwarded to the next stage. If it does not exist in the database, this stage will create a log-file of such words so that they can be added to the database later, then the last stage is the output of signs for each word it fetched from the database and displayed on the screen, these signs are saved in GIF format [7].

A translation system from Arabic text to Arabic sign language was implemented, based on rule-based Interlingua and example-based approaches. It uses SAFAR Platform and ALKHALIL morpho system to extract the morphological properties of each word of the input sentence. Then it generates a video sequence representing the sentence in Arabic sign language based on well-established translation rules and the database of signs. During the translation, if a word of sentence is a proper noun or does not have a correspondence in the database, it will be finger spelled [8].

An automated system was developed that translates Indian speech to Indian Sign Language using Avatar (SISLA). The mechanism operates in three phases: In the first phase, English, Hindi, and Punjabi isolated words are recognized orally in a speaker-independent context. In the second phase, the source language is translated into Indian Sign Language (ISL). In this phase, a HamNoSys based 3D avatar represents the ISL gestures. The four major implementation modules for SISLA include: requirement analysis, data collection, technical development, and evaluation. The multi-lingual feature makes the system more efficient [9].

A framework of a statistical machine translation from English text to American Sign Language (ASL) was designed. This system was based on Moses Tool with few adjustments, and the output was synthesized through a 3D avatar for interpretation. The input text is first converted to gloss, a written version of ASL. Second, the output is provided to the WebSign Plug-in in order to play the sign. The use of a novel language pair, English/ASL, and an advancement in statistical machine translation based on string matching, made possible by Jaro-distance, are contributions of this work [10].

A comparison of the statistical automatic translation system (SATS) and the deep neural automatic translation system (DNATS) was offer whose translates from German text (GR) to Arabic text (AR) in the fixed field. The SATS uses the Noisy Channel procedure. The DNATS uses the deep neural networks the long short-term memory method. The evaluation method used to evaluate the two systems was the BELU method. Demonstrate that the DNATS cannot cost equally as well as the SATS, the future may still be hopeful for (GR-AR) text DNATS [11, 12].

3. BACKGROUND OF ARABIC SIGN LANGUAGE

One of the first ways for the deaf and mute to communicate is sign language, which first arose in Spain in the 17th century to help persons who are unable to talk or hear. It is not limited to the movement of the hands; it includes facial expressions, the movement of the lips and expressions with the movement of the body.

Sign language consists of a group of traditional signs represented by hand signs or spelling using the fingers, in addition to the use of the hands to represent the letters of the alphabet, and it is noteworthy that the signs are usually complete sentences and not just words. Most sign languages are natural languages, differing in structure, so they are verbally close to them, so they are used by deaf people to communicate [13].

Arabic Sign Language is considered a natural language for the Arabian deaf, which has its own structure and rules as explained by the authors in [3], there are many differences between Arabic and sign language such as the verbs and nouns in ArSL are not inflected to show the number and gender agreement. In addition, ArSL typically uses the same sign for verbs, adjectives, and nouns with little change in signing to differentiate a verb from a noun. Unlike Arabic, which inflects verbs and nouns to indicate gender, gender only appears in ArSL with nouns using a separate sign.

For feminine nouns, ArSL uses the girl sign before the noun. For example, "مهندسة" (feminine engineer) is expressed by the sign "بنت" (girl) then followed by the sign "مهندس" (engineer). There are also differences if the word is dual or plural. For word is dual is represented in ArSL with"اثنان" two sign, then a singular word sign or singular word then "اثنان"two sign, for example the word "مدينتان" (cities) is represented in ArSL with "اثنان" (two) sign then "مدينة" (city) sign. The plural word is represented in ArSL with"ثلاثة" three sign, then a singular word sign or singular word sign then "ثلاثة" three sign, for example the word "رجال" (men) is represented in ArSL with the singular word "رجل" (men) then "ثلاثة" three sign. And also, in translating the question in ArSL that represents the question mark, then the rest of the question, then the question word.

In Arabic, sentences can be divided into verbal and nominal sentences. The other types of sentences, such as questions and negations, can be incorporated in their structure. A verbal sentence begins with the verb, and a nominal sentence begins with the subject while, in Arabic Sign Language (ArSL), a sentence begins with the subject. An Arabic verbal sentence can have one of the following structures: Verb–Subject–Object (VSO), Verb-Object-Subject (VOS), Verb-Object (VO), or Verb-Subject (VS). And Arabic nominal sentences have structure Subject–Verb –Object (SVO) or Subject–Verb–Object (SOV) structure, while the Subject–Verb –Object (SVO) order is used as the main word order in nearly all Arabic dialects.

To translate from Arabic-to-Arabic Sign Language (ArSL), the verbal and nominal sentences structures are mapped to the SVO or SOV structures of ArSL; however, the SVO structure is the most common, because ArSL exists in a dialectal environment, which uses SVO as the main structure. Table 1 shows the mapping between Arabic sentences structures and ArSL sentences structures.

Table 1: Mapping Arabic sentences structures and ArSL sentences structures

Arabic	Arabic Sign Language (ArSL)
SVO	SVO or SOV
SOV	SVO or SOV
VOS	SVO or SOV
VSO	SVO or SOV
VS	SV
OSV	SVO or SOV
Dual Nouns	Two+ Noun Or Noun+ Two
Plural Nouns	Three+ Noun Or Noun+ Three

4. THE PROPOSED FRAMEWORK

In this section, we propose an intelligent ArSL framework that exploits machine translation-based deep learning for translating Arabic to sign language. More specifically, our framework considers models based on the main architectures of Transformer Encoder-Decoder. Fig. 1 shows the general structure of the proposed framework. The framework consists of two main phases. The first phase is the translation phase which is responsible for the automatic translation from Arabic to Intermediate Sign language. The second phase is the Sign Sentence Generation phase which is responsible for taking the Intermediate Arabic sign language and generating corresponding Sign language.

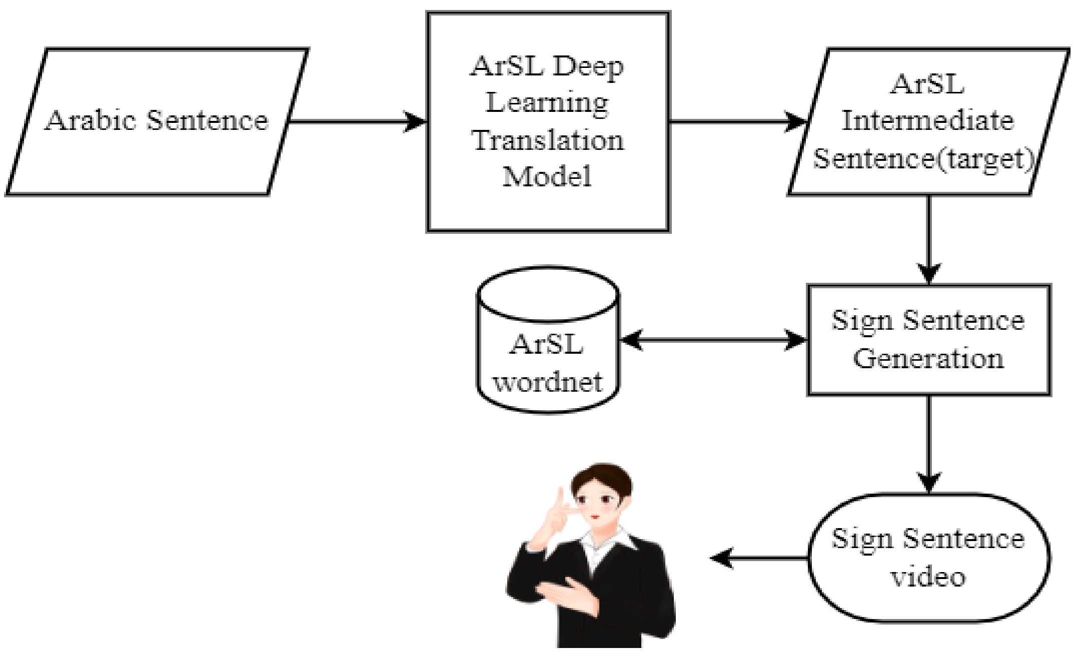

Fig. 1: ArSL Proposed Framework

4.1 Arabic Text Language Translation Phase

For automatic translation from Arabic sentences to intermediate ArSL language and to obtain high accuracy and efficiency, a State-of-the-Art Transformer Encoder-Decoder deep learning architecture is employed. Fig. 2 shows the process of training the translation model. It starts with the data collection and pre-processing phase, which is responsible for cleaning, tokenizing, and vectorizing input Arabic sentences, followed by splitting input data into train and test data then training the model with training data, and finally evaluating the model with different evaluation metrics.

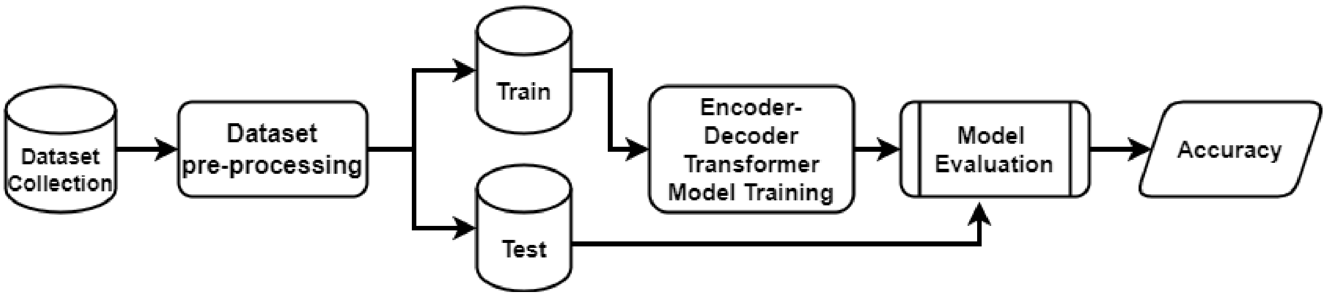

Fig. 2: The Training and Evaluation Process of the Encoder-Decoder Transformer Model

4.2 Dataset overview:

To train and evaluate the Transformer Encoder-Decoder deep transition model, we have built a dataset that consists of 6500 pairs of Arabic sentences; each pair is an Arabic sentence, and its opposite is the intermediate sentence of sign language. We relied on the construction of Arabic sentences on the nominal and the verb only, and we applied the rules of sign language to reach the intermediate sentence of sign language, Intermediate language consists of the Arabic sentence with sign language rules applied, Table 2 shows a few examples of our dataset, We used only two types of sentences in our database, the nominal sentence, and the verbal sentence, The nominal sentence begins with a noun and the verbal sentence begins with a verb. There are four types of verbs in a verbal sentence: the past, the present, the imperative, and the future, these determine the time of the sentence. It is represented in sign language by a sentence tense sign and then the rest of the sentence as explained in the rules of sign language [14] and clarified by the deaf and dumb experts at the Ministry of Education, As we explained in Part Three in Table 1, One base unit of the sentence in building the dataset, if it is verbal or nominal is subject, verb, and objective (SVO).

The books of the Ministry of Education to compile Arabic sentences was used until we reached 3500 sentences, then we used an Arabic Word2Vec model [15] to extract synonyms for the word for the automatic build dataset until we reached 6500 Arabic sentences, and the intermediate sentence of sign language is opposite. The maximum number of words in a sentence is approximately 5 words. Our database will be available online to all researchers and those interested in this field.

Table 2: Examples for translation from Arabic Language to Intermediate ArSL

Arabic Language	Intermediate ArSL
السماء صافية	سماء صافية
يشرب محمد اللبن	مضارع محمد شرب لبن
القمر منير	قمر منير
لعب أخي بالكرة	ماض أخ أنا لعب ب كرة
الزهرتان جميلتان	زهرة اثنان جميلة اثنان
سأسافر بالقطار	مستقبل أنا أسافر ب قطار
الجنود أقوياء	جندي كثير قوي كثير
اذهب إلى المدرسة	أمر أنت ذهب إلى مدرسة
الرجلان صديقان	رجل اثنان صديق اثنان

4.3 Building the Deep Learning Translation Model

A contemporary method for machine translation is deep learning. Unlike traditional machine translation, neural machine translation is a better choice for more accurate translation, and it also provides better performance. For ordinal or temporal issues, such as language translation, natural language processing (NLP), speech recognition, and image captioning, these deep learning algorithms are frequently applied. In our work, we apply the architecture of Transformer's Encoder-Decoder model [16].

4.3.1 The Data Preprocessing Phase

Before the dataset can be modelled and fed to the Encoder-Decoder model, it was prepared by tokenizing an input sentence into distinct elements (tokens) same as is often done for most neural translation models. A tokenized sentence is a fixed-length sequence of 10 tokens, therefore, every sentence will have 10 tokens with trailing paddings, for example the sentence "يشرب محمد اللبن" (which means: Mohamed drinks milk) would look like below after tokenization:

(‘يشرب’, ‘محمد, ‘اللبن’, <pad>, <pad>, <pad>, <pad>, <pad>, <pad>, <pad>)

These tokens are typically integer indices in a vocabulary dataset. So, it may be a sequence of numbers like the below:

(245, 1235, 106, 0, 0, 0, 0, 0, 0, 0)

The number 245 corresponds to the token drink (يشرب), number 1235 corresponds to the token Mohamed (محمد), number 106 corresponds to the token milk (اللبن), and zeros corresponds to trailing paddings.

4.3.2 Transformer's Encoder-Decoder Model

The Transformer's Encoder-Decoder is used in neural machine translation; the input of transformer is sentence (sequence of words), and the output is sentence (sequence of words), as shown in Fig. 3.

Fig. 3: Transformer's Encoder-Decoder input/output

The transformer uses more than one concept in building the model, such as encoder-decoder architecture, word embedding, attention mechanisms, SoftMax. In transformer is used encoder- decoder designer, the output of encoder is features are extracted from input sentence, these features are input of decoder and the decoder uses these features to generate output sentence [16], see Fig. 4.

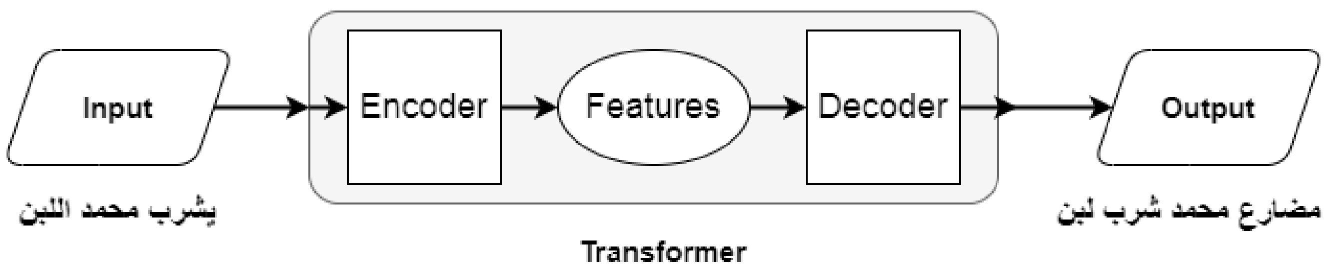

Fig. 4: Encoder-Decoder Block

The encoder in transformer contains multiple encoder blocks. An input sentence goes through the encoder blocks, then the last output product features, this is becoming input to decoder blocks. Also, the decoder contains multiple decoder blocks. Each decoder block receives the features from the encoder, as shown in Fig. 5.

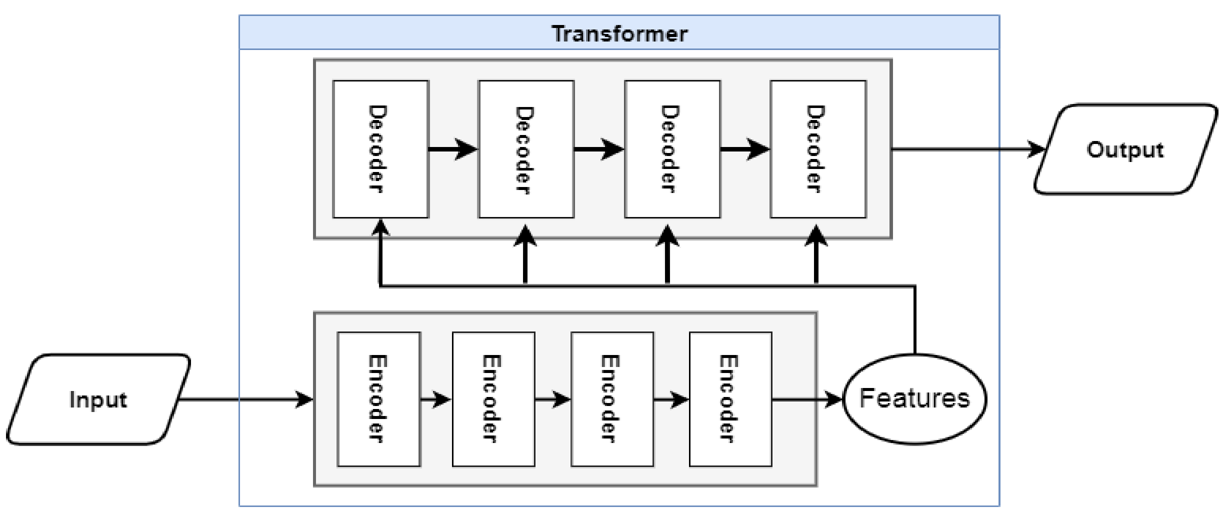

Fig. 5: Encoder-Decoder Structure

Our sequence-to-sequence Transformer consists of a Transformer Encoder and a Transformer Decoder chained together. To make the model aware of word order, we also use a Positional Embedding layer.

The source sequence will be passed to the Transformer Encoder, which will produce a new representation of it. This new representation will then be passed to the Transformer Decoder, together with the target sequence so far (target words 0 to N). The Transformer Decoder will then seek to predict the next words in the target sequence (N+1 and beyond), Fig.6 shows Block Diagram of Encoder-Decoder Transformer Architecture.

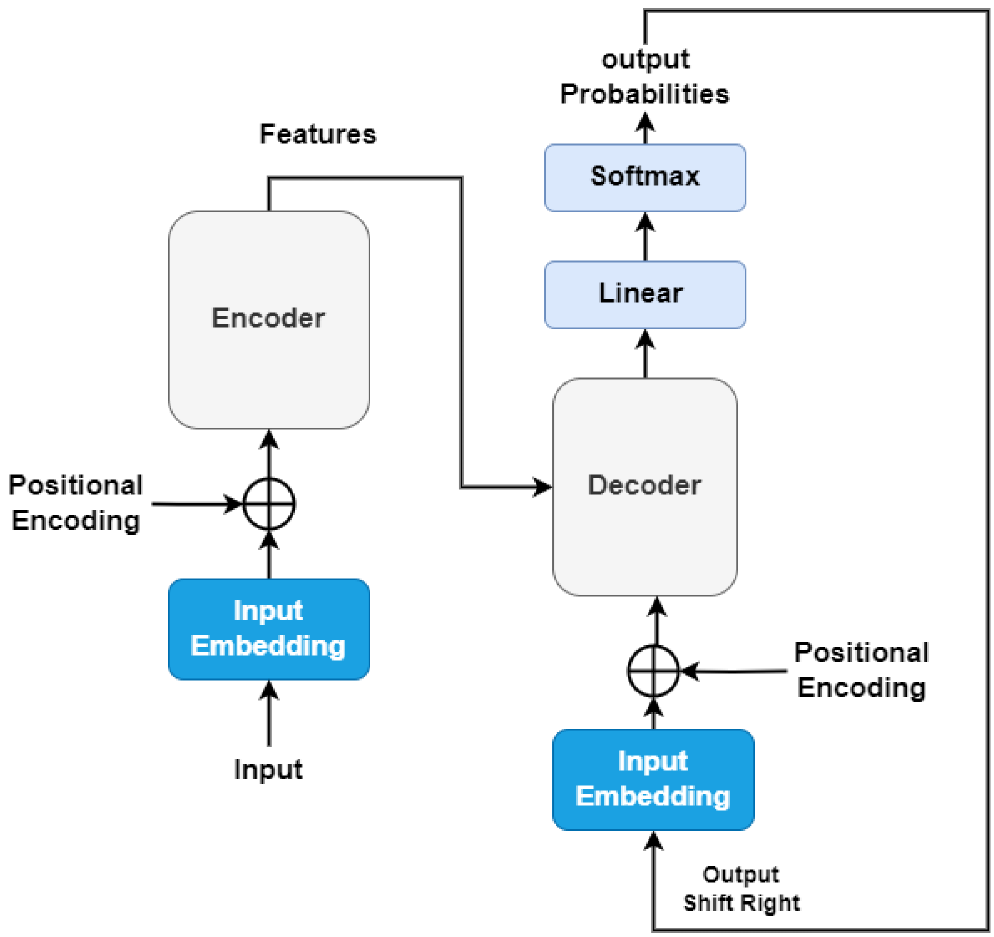

Fig. 6: Block Diagram of Encoder-Decoder Transformer Architecture

4.4 Sign Sentence Generation

After obtaining the intermediate sentence (Target), it will arrange its words, and the output for the user will be in the form of a sequential sequence of videos for the words of the sentence. We designed about 150 signs on the E sign [17] program for making 3D signs Builder PC then we convert the extension of these videos from (gbr) to (mp4) to easily open with GUI forms. And, built an Arabic Sign word net dataset through synonyms for each word, all of them have one sign, and this ensures that most of the words are available in the database and can be translated easily for the user. The size of the database reached about 400 words, with a total of one reference for every four words as shown in Table 3, these pictures are for illustration only.

Table. 3: Sample of Arabic Sign Word Net

Word	Sign
شكرا	
إمتنان	
عرفان	
عائلة	
أسرة	

5. EXPERIMENTAL EVALUATION

5.1 Performance Metrics

The proposed deep translation model is evaluated using the most common metrics that can be defined as follows:

1- Bilingual evaluation understudy (BLEU) is an automatic evaluation metric used to measure the similarity of the hypothesis to the reference [18]. BLEU is calculated through three factors: (1) n-gram-based precision of the machine translation output and the reference translation, (2) brevity penalty (BP) to prevent overfitting of sentence length, and (3) clipping for calibration of continuous word appearance.

2- Accuracy is calculated as the sum of two accurate predictions (True Positive + True Negative) divided by the total number of data sets. The best accuracy is 1.0, and the worst is 0.00 [19].

3- Loss is defined as the difference between the predicted value model and the true value. The most common loss function used in deep neural networks is cross-entropy [19].

5.2 Experimental Results and Discussion

Google Colaboratory or Google Colab [20] in short was used as our integrated development environment (IDE) with a K80 GPU and 12 GB memory. The proposed framework is implemented using a Python environment on a Linux platform with TensorFlow and Keras. The experiment was carried using our proposed dataset, as we mentioned before the dataset consists of 6500 pairs of Arabic sentences; each pair is the Arabic sentence, and its opposite is the intermediate sentence of sign language. Data for training and testing are separated from the dataset. The training data is then fed to Transformer's Encoder-Decoder deep learning model, testing data is then used to evaluate our model.

Fig. 7 shows that the accuracy of Transformer's Encoder-Decoder model is getting better while increasing the dataset as it starts with 65% accuracy using dataset 3600 sentences then 67% using 4200 sentences, and finally it became 72% using 6500 sentences. Therefore, we are willing to increase our dataset to reach the highest possible accuracy, Fig. 8 and Fig. 9 show the accuracy and loss of our best model 72%.

For the test dataset we used the BLEU metric to evaluate our proposed model. The model achieved an average BLEU score of 69% on the test data, Fig. 10 shows a sample of resulted BLEU scores.

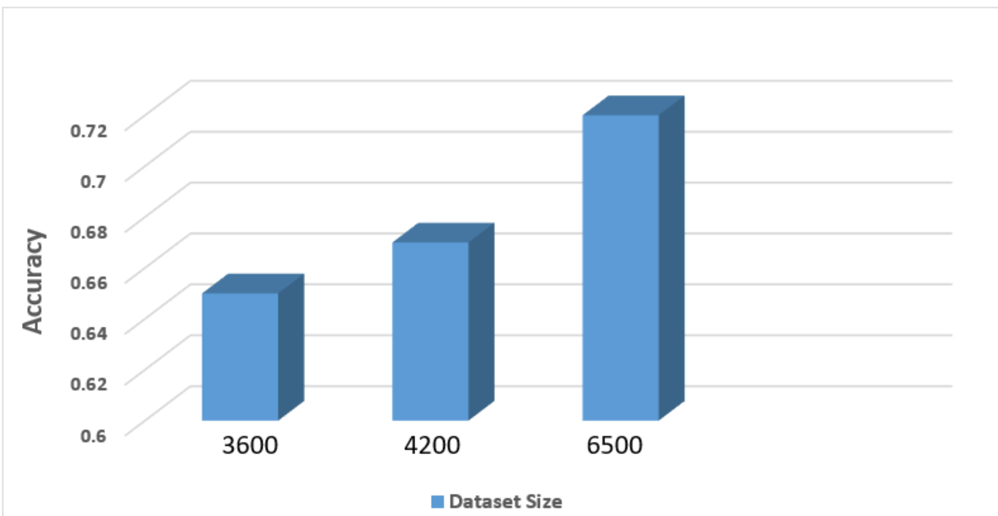

Fig. 7: Datasets Accuracies for Different Datasets Sizes with Encoder-Decoder Transformer

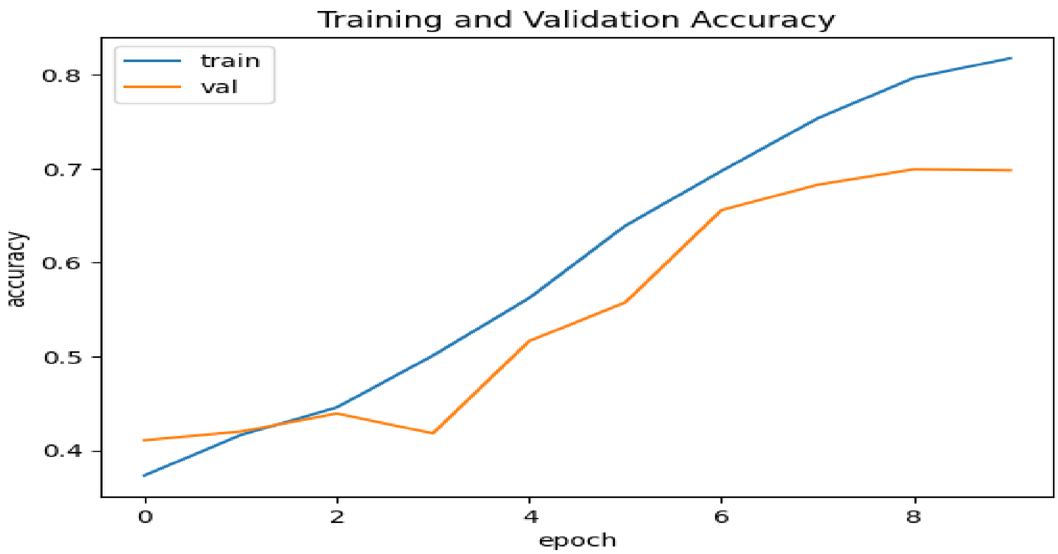

Fig. 8: Encoder-Decoder Transformer Model Accuracy

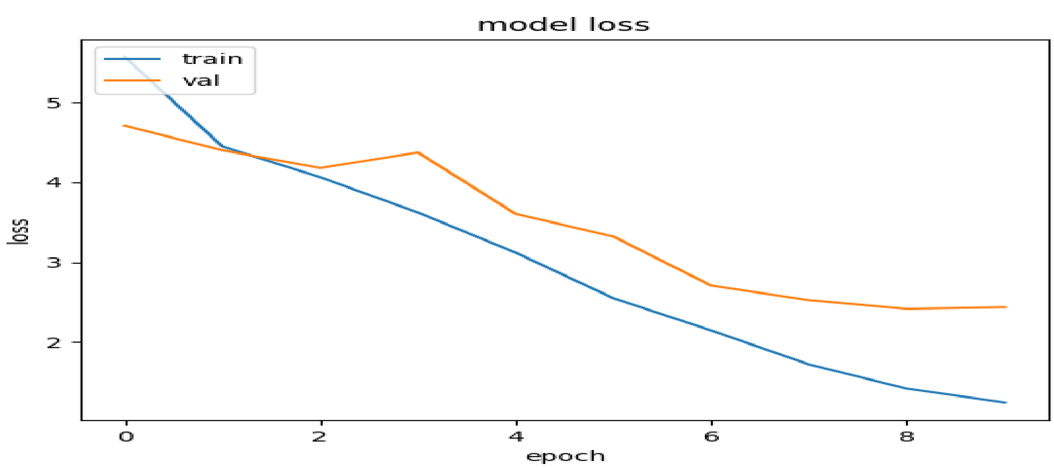

Fig. 9: Encoder-Decoder Transformer Model Loss

input_sentence: الأشجار ملتفة translated_sentence: [start] شجرة كثير [end] 23 ref_translated_sentence: [start] شجرة كثير ملتفة [end] 29 bleu_score: 0.8	input_sentence: جلس الطفل على الطاولة translated_sentence: [start] ماض طفل حصل على طاولة [end] 35 ref_translated_sentence: [start] ماض طفل جلس على طاولة [end] 35 bleu_score: 0.8571428571428571	input_sentence: الشجرة مثمرة translated_sentence: [start] شجرة مثمرة [end] 24 ref_translated_sentence: [start] شجرة مثمرة [end] 24 bleu_score: 1.0

Fig. 10: A Sample of BLEU scores

SUMMARY AND CONCLUSIONS

In this paper, we have presented our system based on neural translation system, a system that is implemented using Encoder-Decoder Transformer Architecture. The system is trained using a dataset containing about 6500 different types of sentences (nominal and verbal). Word net of ArSL To get synonyms and increase the size of the dataset. The accuracy of the system was about 0.72 with error rate of 0.28. This accuracy can be increased by increasing the size of the dataset. The model achieved an average BLEU score of 69% on the test data. The accuracy can be also increased through increasing the diversity of the types of sentences in the database to include declarative, interrogative, and exclamatory.

CONFLICT OF INTEREST

The authors have no financial interest to declare in relation to the content of this article

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