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Translating Sumerian Symbols into French Letters

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A B S T R A C T

Sumerian symbols, which look like cuneiform letters, were used in a very old writing style. In this paper, a new method to translate the Sumerian symbols into French letters is introduced. It is based on the Cascade-Forward Neural Network (CFNN). The CFNN is exploited and adapted for the translation issue. It accepts a cuneiform letter image as an input and produces an appropriate output that refers to the translated french letter. Reasonable image augmentations are employed. These augmentations are for the: left direction rotations, right direction rotations and multiple translation directions (to the left, right, bottom and top). Total of 780 images are utilized for rotations and 338 images are collected for translations. This work can successfully attain the performance of 100%.

1. GENERAL BACKGROUND

Sumerian language is a very old language, it began in 3000 B.C. as it was established by an Iraqi civilization called Sumer. Sumerian symbols writing style were look like nail shapes. These symbols were employed to state previously happened actions, events and other information [1]. Generally, they were firstly used for rebusing nouns. Later, the scribes located the Sumerian symbols into appropriate orders. After that, the prior contexts were having better structures [2]. Specifically, cuneiform symbols were used in Sumerian writing [3]–[7].

Sumerian symbols developed during many stages to characterise the shape of numbers and letters. Assyrian and Babylonian languages of nail shapes are represent the enhancement of old Sumerian writing. In Iraq, too many tablets of Sumerian symbols were discovered at the early stage of 19th century. Different Babylonian and Assyrian writings were provided in these tablets. Many museums are currently show tablets of Sumerian symbols. Expectedly, translating Sumerian symbols needs time and experience. Nevertheless, to sort translating problems out the information technology is necessary [8].

Several studies focused on translating Sumerian symbols by utilizing Artificial Intelligence (AI) methods. In 2000, Sulaiman illustrated the Acadian and Sumerian writing by using the gained expertise [1]. It appears that a classical method was exploited for translating the Acadian and Sumerian writings into known Arabic language. In 2007, Postgate arranged a set of knowledge concerning Iraqi languages as the Sumer language. Benificial highlights were provided for Sumerian writing style as phonology, syntax, nominals, lexical categories, verbs, pronouns and adjectives [8]. Similarly, the language was classically analyzed by using the gained expertise. In 2010, Yushu described how the writing invention was taking into account by Sumerian [9]. It seems that classical translating was also exploited here. In 2017, Aktas and Asuroglu introduced a study that utilizes computer techniques for reading signs of nail shapes. Fundamentally, Hittite writing was utilized for the signs of nail shapes. Also, classification and clustering algorithms were exploited as data mining [10]. Clearly, the Sumerian symbols did not be used in this study. In 2019, Saeid *et al.* recognized letters of nail shapes by utilized the Support Vector Machine (SVM). Image processing operations were employed before applying the SVM [2]. Obviously, this work did not focuse on translating as it concentrated on recognizing the considered letters. Also in 2019, Born *et al.* analyzed undeciphered proto-Elamite scripts by exploiting computational linguistic methods. Latent Dirichlet Allocation (LDA), n-gram frequencies and hierarchical clustering models were used. Performances were obtained by exposing priorly-unobserved relationships of deciphering manual and signs [11]. In 2020, Gordin *et al.* concentrated on Reading cuneiform of Akkadian. Natural Language Processing (NLP) was utilized. Furthermore, Recurrent Neural Network (RNN) was highly evaluated [12]. In 2021, Hamdany *et al.* introduced a machine learning method for translating cuneiform symbols into English. The machine learning was backpropagation neural network [13]. In 2022, Al-Obaidi *et al.* presented a novel method for interpreting alphabet letters of Iraqi sign language. A deep learning model called the Deep Recurrent Alphabet Sign Language (DRASL) was provided. Hardware of glove and sensors were exploited [14][15]. In 2023, Gutherz *et al.* illustrated translating Akkadian language into English. Convolutional Neural Network (CNN) was used as NLP for the case of translation [12]. In this study, clustering various symbols were considered. It can be observed that there was no prior work that focused on translating the Sumerian symbols into French letters by utilizing the Cascade-Forward Neural Network (CFNN). This paper will consider this and present a main contribution for this issue. Indexing and abstracting services depend on the accuracy of the title, extracting from it keywords useful in cross-referencing and computer searching. An improperly titled paper may never reach the audience for which it was intended, so be specific.

The goal of this work is translating the Sumerian symbols into French letters. It depends on the CFNN which is adapted and utilized for the translation issue. The remaining sections in this paper are distributed as follows: Section 2 states the methodology, Section 3 demonstrates results and Section 4 provides the conclusion.

2. SUGGESTED TRANSLATION METHOD

In this study, a suggested translation method based on the CFNN has been designed and adopted. It has the cabability to translate the images of Sumerian symbols into French letters. The main idea of the suggested CFNN is obtaining a Sumerian symbol image and referring to its assigned French letter. Then, French letters can be produced from Sumerian symbol images. Neural networks of multi-outputs as in [16] could be found valuable. Fig. 1 shows a flowchart of comprehensive translation steps. Fig. 2 demonstrates the main CFNN architecture of our proposed method.

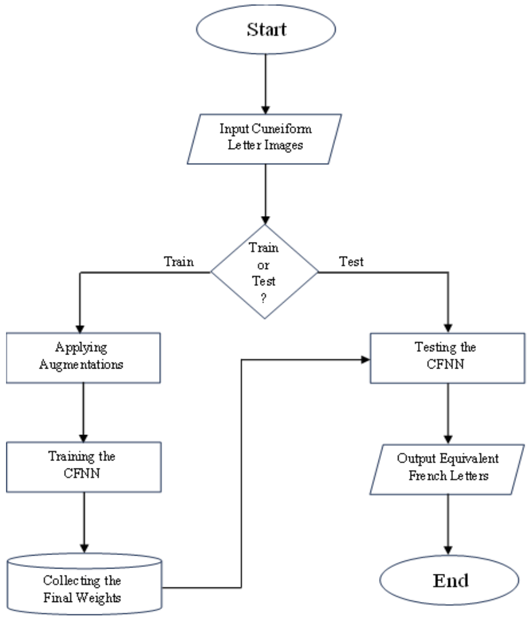


Figure 1. A flowchart of comprehensive translation steps

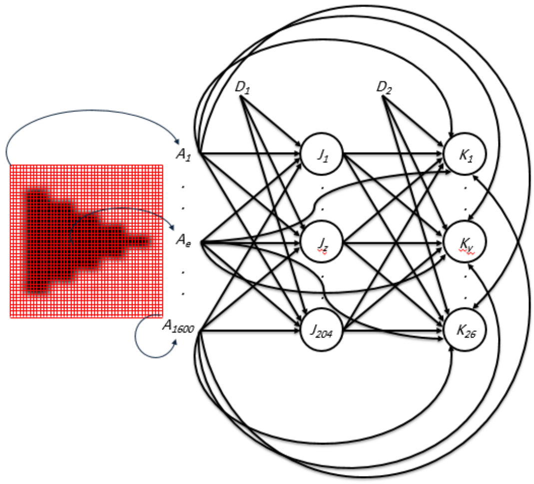


Figure 2. The main CFNN architecture of our proposed method

Basically, the CFNN is composed of output layer **K**, hidden layer **J** and input layer **A**. Also, it has various weights' connections. $\mathbf{V^1}$ is the 1st weights connection between **A** and **J** layers. $\mathbf{V^2}$ is the 2nd weights connection between **J** and **K** layers. $\mathbf{V^3}$ is the 3rd weights connection between **A** and **K** layers. Furthermore, two phases are required, training phase and testing phase. The values of $\mathbf{V^1}$, $\mathbf{V^2}$ and $\mathbf{V^3}$ begin with small randoms at the training start. Nonetheless, the last values of $\mathbf{V^1}$, $\mathbf{V^2}$ and $\mathbf{V^3}$ are saved at the training end. These last values are used at the testing start [17]. Essential CFNN equations are illustrated in [18][19], they are expressed as follows:

$$Jin_z = D_{0z}^1 + \sum_{e=1}^{q} A_e V_{ez}^1 \tag{1}$$

where Jin_z represents a hidden layer input value, z represents the hidden neurons index, D_{0z}^1 represents a weight between the hidden and 1st bias nodes, q represents the input neurons number, e represents the input neurons index, A_e represents an input layer value, and V_{ez}^1 represents a weight between the hidden and input layers.

$$J_z = f(Jin_z) \tag{2}$$

where J_z represents a hidden layer outcome value.

$$Kin_y = D_{0y}^2 + \sum_{z=1}^{r} J_z V_{zy}^2 + \sum_{e=1}^{q} A_e V_{ey}^3 \tag{3}$$

where Kin_y represents an output layer input value, y represents the output neurons index, D_{0y}^2 represents a weight between the output and 2nd bias nodes, r represents the hidden neurons number, V_{zy}^2 represents a weight between the output and hidden layers, and V_{ey}^3 represents a weight between the output and input layers.

$$K_y = f\left(Kin_y\right) \tag{4}$$

where K_y represents an output layer outcome value.

$$\varphi_y = (T_y - K_y) f'(Kin_y) \tag{5}$$

where φ_y represents a computed main error and T_y is an assigned target.

$$\Delta V_{zy}^2 = \mu\, \varphi_y\, J_z \tag{6}$$

where ΔV_{zy}^2 represents a weight change between the output and hidden layers, and μ represents the learning rate.

$$\Delta V_{ey}^3 = \mu\, \varphi_y\, A_e \tag{7}$$

where ΔV_{ey}^3 represents a weight change between the output and input layers.

$$\Delta D_{0y}^2 = \mu\, \varphi_y \tag{8}$$

where D_{0y}^2 represents a weight change between the output and 2nd bias nodes.

$$\varphi in_z = \sum_{y=1}^{s} \varphi_y V_{zy}^2 \tag{9}$$

where φin_z represents a computed secondary input error of the hidden layer and s represents the output neurons number.

$$\varphi_z = \varphi in_z\, f'(Jin_z) \tag{10}$$

where φ_z represents a computed secondary error of the hidden layer.

$$\Delta V_{ez}^1 = \mu\, \varphi_z\, A_e \tag{11}$$

where ΔV_{ez}^{1} represents a weight change between the hidden and input layers.

$$\Delta D_{0z}^{1} = \mu \, \varphi_{z} \tag{12}$$

where ΔD_{0z}^{1} represents a weight change between the hidden and 1st bias nodes.

$$V_{ez}^{1}(new) = V_{ez}^{1}(old) + \Delta V_{ez}^{1} \tag{13}$$

$$V_{zy}^{2}(new) = V_{zy}^{2}(old) + \Delta V_{zy}^{2} \tag{14}$$

$$V_{ey}^{3}(new) = V_{ey}^{3}(old) + \Delta V_{ey}^{3} \tag{15}$$

$$D_{0z}^{1}(new) = D_{0z}^{1}(old) + \Delta D_{0z}^{1} \tag{16}$$

$$D_{0y}^{2}(new) = D_{0y}^{2}(old) + \Delta D_{0y}^{2} \tag{17}$$

Equations (1-4) are utilized in the CFNN testing phase, however, the last obtained training values of weights are used.

In this work, q is equal to 1600 which is sufficient to all Sumerian symbol image pixels, r is equal to 204 where this is calculated according to [20] and s is equal 26 as this represents the number of French alphabets.

Consequently, French letters can simply be generated from Sumerian symbol images. The proposed translation method is reasonable to translate Sumerian symbols into the assigned French letters.

3. RESULTS AND DISCUSSIONS

First of all, Sumerian symbols with their assigned French letters are required. Table 1 demonstrates a useful representation for the Sumerian symbols and their assigned French alphabets.

Sumerian symbol images are exploited here. Each image has a Two-Dimensional (2D) size of 40 × 40 pixels. This size is reshaped to the One-Dimensional (1D) size of 1600 × 1 pixels which corresponds to the CFNN input nodes. So, there is a suitable adaptation between the CFNN input nodes and a Sumerian symbol image. Since there are few Sumerian symbol images, image augmentations are used to each one of them. Therefore, a big number of training samples are provided and the efficiency of the suggested method is expectedly increased. Various augmentations of translations and rotations can be employed according to [21]–[24]. Table 2 shows examples of established translating and rotating training Sumerian symbol images.

Table 1. Useful representation for the Sumerian symbols and their assigned French alphabets

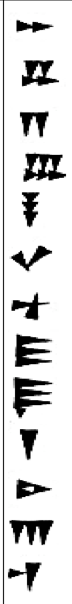
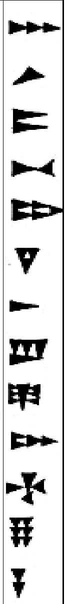
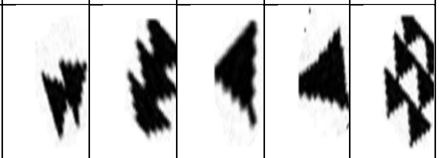
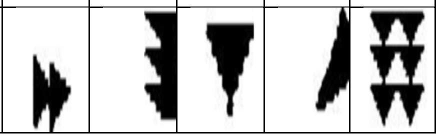
French Alphabet	French Letter	Sumerian Symbol	French Alphabet	French Letter	Sumerian Symbol
ah	A		en	N	
beh	B		oh	O	
seh	C		peh	P	
deh	D		koo	Q	
uh	E		air	R	
eff	F		ess	S	
zheh	G		teh	T	
ahsh	H		ooh	U	
ee	I		veh	V	
zhee	J		doo-blah-veh	W	
kah	K		eeks	X	
ell	L		eegrek	Y	
em	M		zed	Z	

Table 2 . Eexamples of established translating and rotating training Sumerian symbol images

Augmentation Operation	1st Symbol	2nd Symbol	3rd Symbol	4th Symbol	5th Symbol
Rotations					
Translations					

This table provides examples of the used operations to images of Sumerian symbols. Various translations and rotations are implemented for each Sumerian symbol image. Total of 780 images are collected for the two directional rotations. That is, 390 images are acquired for left direction rotations and 390 images are acquired for right direction rotations. Moreover, Total of 338 images are collected for various translation directions (left, right, bottom and top). The acquired augmentation images are utilized for the training phase.

Training parameters of the CFNN are selected as follows: training type Scaled Conjugate Gradient (SCG) [25], binary sigmoid activation function in the hidden layer, linear activation function in the output layer and minimum training error equal to 0.001. The most important parameters that are utilized for the CFNN are given in Table 3. Fig. 3 shows the CFNN performance during the training phase.

Table 3. Important parameters that are utilized for the CFNN

Parameter	Value
Training type	SCG
Activation function in the hidden layer	Binary sigmoid
Activation function in the output layer	Linear (pure linear)
Minimum training error	0.001
Number of input nodes	1600
Number of hidden nodes	204
Number of output nodes	26

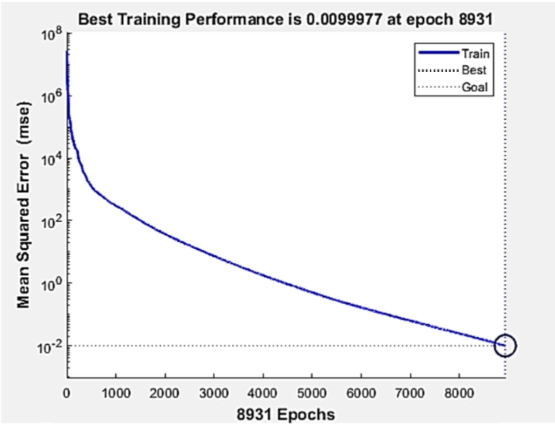
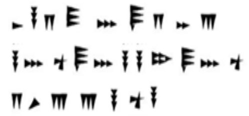
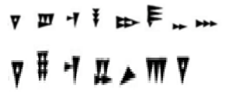


Figure 3. The CFNN performance during the training phase

From this figure, it can be seen that the training curve is efficiently degrades toward a very small error value of 0.00099977. This indicates the successfulness and acceptability of the training phase.

Sumerian symbols can effectively be translated from images into referral French letters in the CFNN testing phase. Subsequently, French letters can easily be produced. A remarkable high accuracy of 100% can be achieved by applying the suggested translation method. Table 4 demonstrates multiple French writings which can be obtained from Sumerian symbols by employing our proposed translation method**.**

Table 4. Multiple French writings which can be obtained from Sumerian symbols by employing our suggested translation method

Sumerian Symbols	French Letters
	**MODREN SCIENTIFIC RESEARCHES**
	**TECHNICAL ENGINEERING COLLEGE**
	**NORTHERN TECHNICAL UNIVERSITY**
	**SUMERIAN SYMBOLS**

4. PAPER'S CONCLUSION

In this paper, a new method to translate Sumerian symbols into French letters was introduced. It is based on the CFNN, which was designed and adopted for the proposed translation. The translation method has considered converting Sumerian symbol images into their determined French letters. Various image augmentations were applied. These are different rotation angles to the left direction, different rotation angles to the right direction and different translation directions to (the left, right, bottom and top). Thus, big numbers of images were provided. That is, 780 images are acquired for rotations and 338 images are acquired for translations. The CFNN required two phases of training and testing. Augmented images were employed in the training phase. Consequently, the CFNN has the capability to obtain correct indicatorts for the applied Sumerian symbol images into their assigned French letters during the testing phase. Subsequently, French letters can be provided with remarkable high accuracy of 100%.

For future work, adding the image processing of scaling can be employed and translating Sumerian symbols into Arabic language letters can be suggested as the next aim.

REFERENCES

[1] A. Sulaiman, *Cuneiform Writing*. Dar Al-Kutubfor Printing and Publishing – Mosul, 2000.
[2] A. A. Saeid and A. M. S. Rahma, "Cuneiform symbols recognition by support vector machine (SVM)," *Journal of AL-Qadisiyah for computer science and mathematics*, vol. 11, no. 1, p. Page-1, 2019.
[3] S. Dalley, "The Invention of Cuneiform: Writing in Sumer," *Technology and Culture*, vol. 46, no. 2, pp. 408–409, 2005.
[4] I. Finkel, "Strange byways in cuneiform writing," in *The Idea of Writing*, Brill, 2009, pp. 7–25.
[5] A. E. Gnanadesikan, *The writing revolution: Cuneiform to the internet*, vol. 8. John Wiley & Sons, 2008.
[6] C. B. F. Walker, *Cuneiform*, vol. 3. Univ of California Press, 1987.
[7] J.-J. Glassner, *The invention of cuneiform:*

writing in Sumer. JHU Press, 2003.

[8] J. N. Postgate, *Languages of Iraq, ancient and modern*. British School of Archaeology in Iraq, 2007.

[9] G. Yushu, "The Sumerian Account of the Invention of Writing—A New Interpretation," *Procedia-Social and Behavioral Sciences*, vol. 2, no. 5, pp. 7446–7453, 2010.

[10] A. Z. Aktas and T. Asuroglu, "Computerized hittite cuneiform sign recognition and data mining application examples," *European International Journal of Science and Technology*, 2017.

[11] L. Born, K. Kelley, N. Kambhatla, C. Chen, and A. Sarkar, "Sign clustering and topic extraction in Proto-Elamite," in *Proceedings of the 3rd Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*, 2019, pp. 122–132.

[12] G. Gutherz, S. Gordin, L. Sáenz, O. Levy, and J. Berant, "Translating Akkadian to English with neural machine translation," *PNAS nexus*, vol. 2, no. 5, p. pgad096, 2023.

[13] A. H. S. Hamdany, R. R. Omar-Nima, and L. H. Albak, "Translating cuneiform symbols using artificial neural network," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 19, no. 2, pp. 438–443, 2021.

[14] A. S. I. Al-Obaidi, R. R. O. Al-Nima, and T. Han, "Interpreting Arabic sign alphabet by utilizing a glove with sensors".

[15] A. Al-Obaidi, R. Al-Nima, and T. Han, *Interpreting the Sign Language of the Arabic Alphabet*. LAP Lambert Academic Publishing, 2022.

[16] M. T. Al-Kaltakchi, R. R. Omar, H. N. Abdullah, T. Han, and J. A. Chambers, "Finger texture verification systems based on multiple spectrum lighting sensors with four fusion levels," *Iraqi Journal of Information and Communication Technology*, vol. 1, no. 3, pp. 1–16, 2018.

[17] L. V Fausett, *Fundamentals of neural networks: architectures, algorithms and applications*. Prentice-Hall, Inc., 1994.

[18] R. R. O. Al-Nima, F. H. Abdulraheem, and M. Y. Al-Ridha, "Using Hand-Dorsal Images to Reproduce Face Images by Applying Back propagation and Cascade-Forward Neural Networks," in *2nd International Conference on Electrical, Communication, Computer, Power and Control Engineering, ICECCPCE 2019*, 2019. doi: 10.1109/ICECCPCE46549.2019.203755.

[19] F. M. Shehab, R. R. Omar, and R. Y. Sedik, "Estimating Reference Evapo-transpiration in Mosul (Iraq) Using Cascade Neural Networks," *Eng. & Tech. Journal*, vol. 32, no. 9, pp. 2277–2285, 2014.

[20] K. Shibata and Y. Ikeda, "Effect of number of hidden neurons on learning in large-scale layered neural networks," in *2009 ICCAS-SICE*, IEEE, 2009, pp. 5008–5013.

[21] E. D. Cubuk, B. Zoph, D. Mane, V. Vasudevan, and Q. V Le, "Autoaugment: Learning augmentation strategies from data," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 113–123.

[22] S. Shang, L. Long, S. Lin, and F. Cong, "Automatic zebrafish egg phenotype recognition from bright-field microscopic images using deep convolutional neural network," *Applied Sciences*, vol. 9, no. 16, p. 3362, 2019.

[23] M. J. Mohammed, E. A. Mohammed, and M. S. Jarjees, "Recognition of multifont English electronic prescribing based on convolution neural network algorithm," *Bio-Algorithms and Med-Systems*, vol. 16, no. 3, p. 20200021, 2020.

[24] Y. Lu, "Food image recognition by using convolutional neural networks (cnns)," *arXiv preprint arXiv:1612.00983*, 2016.

[25] M. F. Møller, "A scaled conjugate gradient algorithm for fast supervised learning," *Neural networks*, vol. 6, no. 4, pp. 525–533, 1993.