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Neural Machine Translation of Spanish-English Food Recipes Using LSTM

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***Abstract*—Nowadays, food is one of the things that has been globalized, and everyone from different parts of the world has been able to cook food from other countries through existing online recipes. Based on that, this study developed a translation formula using a neural machine translation (NMT). NMT is a recently proposed approach to machine translation. Unlike the traditional statistical machine translation, the neural machine translation aims at building a single neural network that can be jointly tuned to maximize the translation performance. The models proposed recently for neural machine translation often belong to a family of encoder–decoders. Our experiment led to novel insights and practical advice for building and extending NMT with the applied long short-term memory (LSTM) method to 47 bilingual food recipes between Spanish-English and English-Spanish. LSTM is one of the best machine learning methods for translating languages because it can retain memories for an extended period concurrently, grasp complicated connections between data, and provides highly useful information in deciding translation outcomes. The evaluation for this neural machine translation is to use BLEU. The comparing results show that the translation of recipes from Spanish-English has a better BLEU value of 0.998426 than English-Spanish with a data-sharing of 70%:30% during epoch 1000. Researchers can convert the country's popular cuisine recipes into another language for further research, allowing it to become more widely recognized abroad.**

***Keywords*—Natural language processing; neural machine translation; food recipes; LSTM.**

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I. INTRODUCTION

Food is fundamental to human life, and it provides energy and defines each country's distinctive local identity and culture [1]. Along with cultural globalization, the food available in every country has now spread widely [2], [3]. In today's digital era, many people share the food figures they eat on social media [4], [5]. So that the demand for unique food recipes from each country around the world is increasing, which can be seen from the increasing number of recipe data available online on the web in recent years [6].

The recipes come from worldwide and are written in multiple languages, including Spanish. However, language barriers can make it difficult to find local specialties [7]. In particular, Spanish food is becoming increasingly popular and famous due to its authentic taste [8]. Some typical Spanish foods that are already worldwide and much loved are Churros, Paella Valenciana, Tortilla Espanolla, Patatas Bravas, Fideua, Croquetas, Cream Catalina, Empanadas, etc [9]. Many people use these Spanish food recipes if the recipes are translated into another universal language such as English.

One possible solution is to use machine translation. Machine translation is the process of translating content from one language (the source) to another (the target) without the need for human intervention [10]. The first generation of machine translation is rule-based machine translation (RBMT). Rule-based machine translation is a machine translation paradigm in which an expert encodes linguistic knowledge as rules that translate from source to target language [11]. Many rules must be added to improve quality, resulting in a complex system [12]. Linguistic analysis was carried out on the input source sentences to extract information in terms of morphology, parts of speech, phrases, named entities, and word disambiguate [13], [14] . The second type is example-based machine translation (EBMT). The EBMT stores examples of previous translations in the aligned bilingual corpus [15]. If the match is large enough, examples produce well-structured output, but the generated text is often incoherent [16]. Next is statistical machine translation (SMT) translates text into target based on a statistical model. SMT assumes that the word from the target language is a translation of the source language word set with several possibilities [17], [18]. Decoding complexity and target language reordering are two significant concerns with SMT [19]. The last is neural machine translation (NMT), a fully automated neural network-based translation technology. Rather than translating each word on its own, NMT provides a more accurate translation by considering the context in which it is used [20], [21].

NMT architectures rely heavily on encoders and decoders [22]–[24]. Long short-term memory (LSTM) based methods, recurrent neural network (RNN) based methods, convolution neural network (CNN) based methods, and self-attention network (SAN) based methods are all examples of robust encoders and decoders. Therefore, in this study, NMT, based on the LSTM model encoder-decoder, translates Spanish food recipes into English. LSTM is the best option because it allows inputting a sentence rather than just one word as an input for prediction, which is much more convenient and efficient in NMT [25]. This method also was repeated in the opposite language, English to Spanish. This study used training and testing data variations and the epoch. Finally, the results were evaluated using BLEU consisting of BLEU 1 to 4.

II. Material and Methods

The first stage of this research was data collection. After data collection, the general process was conducted in the form of preprocessing, split text, model building, and evaluation. The process and details of the stages are explained in more detail in the following subchapter.

A. Data Collection

The dataset used is Bilingual Language English and Spanish Recipe Cards data obtained from https://gabhousewife.blogspot.com/2012/02/bilingual-recipe-cards-english-spanish.html. It has 47 recipe menus containing 1057-word pairs, each written using the same structure consisting of recipe name, service, ingredients, directions, and serving suggestions, as shown in Fig. 1.

English	**Spanish**
'Black Beans'	'Frijoles Negros Refritos'
Serves: 10	Porciones: 10
Ingredients: • 2 packs Isadora refried Black Beans • 1 dash of Maggi seasoning sauce • pepper to taste • 1 tsp mashed garlic • 3 tbsp tomato puree • ½ tsp vegetable oil	Ingredientes: • 2 paq de frijoles negros refritos Isadora • 1 cdta jugo Maggi • pimienta al gusto • 1 cdta ajo picado • 3 cuch puré de tomate • ½ cdta aceite vegetal
Directions: 1. Heat the oil and the garlic. 2. Place the beans and stir. 3. When heated, add the tomato puree, pepper, and Maggi seasoning sauce. 4. Keep stirring until cooked, like 5 minutes. 5. Serve in serving plate and top with fresh shredded cheese.	Receta: 1. Calienta el aceite y el ajo 2. Agrega los frijoles y revuelve. 3. Cuando caliente, agrega el puré de tomate, la pimienta y el jugo Maggi. 4. Continua revolviendo hasta que cosa, cerca de 5 minutos. 5. Sirve en el platón donde lo servirás y espolvorea queso.
Serving Suggestion: Serve with corn tortillas or Pastel Azteca or Tacos Chilorio or Tarto de Cochinita Pibil.	Sugerencia para Servir: Serve with corn tortillas or Pastel Azteca or Tacos Chilorio or Torta de Cochinita Pibil.

Fig. 1 Examples of 2-Language Recipes

The sample dataset takes 4 sample recipes with the names Almond-ed Rice, Bacon & Potato Chunky Cream, Beef Taquitos, and Black Beans, which then obtained the number of words in each structure based on the English recipe can be seen in Table I.

TABLE I
NUMBER OF WORDS ON RECIPE STRUCTURE

No.	Structure	Minimum Word	Maximal Word
1.	Recipe Name	2	5
2.	Serves	2	2
3.	Ingredients	2	15
4.	Directions	4	24
5.	Serving Suggestion	8	21

Based on Fig. 1 and Table I, there are findings obtained, namely (1) There are punctuation marks, (2) The text contains uppercase and lowercase letters, (3) There are special characters in Spanish, (4) There are word structures in English. English with different translations in Spanish. From some of these findings, it is necessary to preprocess the dataset used.

B. Data Preprocessing

Preprocessing is an essential step in natural language processing (NLP). The primary purpose of preprocessing is to create dictionaries that index the words present in the training and validation datasets [26]. Preprocessing converted the document into a more digestible form so that machine learning algorithms can work better [27]. Preprocessing in this study uses the cleaning text operation in Fig. 2.

```
Start
  Sorting
  Normalize unicode characters
  Tokenize on white space
  Convert to lowercase
  Remove punctuation from each token
  Remove non-printable chars from each
  token
End
```

Fig. 2 Preprocessing Cleaning Text Pseudocode

Sorting is done based on the number of words available [28]. From Table 1, the minimum number of words was in the top position, and the maximum number of words was in the bottom position according to the order of the number of words. Sorting is done without changing the meaning of the translation. This sorting does not delete the exact words; for example, Ingredients (Spanish: Ingredientes) which appear 50 times, are not filtered or deleted so that the training results in better translations.

Normalization is done using normalized Unicode characters, which convert string vectors using Normalization Form Canonical Decomposition (NFD) [29]. In NFD, characters are decomposed by canonical equality, and some combination characters are arranged in a particular order [30].

Tokenization is used to aid in understanding context by breaking raw text into small pieces (tokens) [31]. Tokenization in this study uses a white space tokenization technique that breaks sentences into meaningful words [32]. Case folding was done by converting to lowercase. The purpose of lowercase is to convert all letters in the document to lowercase, from ’a' to 'z' [33]. Noise removal is used to remove punctuation marks and non-printable characters, such as [!”#$%&’()*+,-./:;ó?@\^_`{|}~] [34]. In this study, no process was carried out to remove the remaining un alphabetic tokens because this recipe dataset was unique. The ingredients had the size of the dose presented using numbers.

C. Split Text

This study used a combination of 47 existing recipe menus, then sorted according to the length of the word and repeated words. So, from the results of preprocessing that has been done, 3000 sentences were distributed data in this process. This study's training and testing data distribution has three scenarios, as shown in Fig. 3. In testing data, the data is taken based on the order of the sorting results with many words.

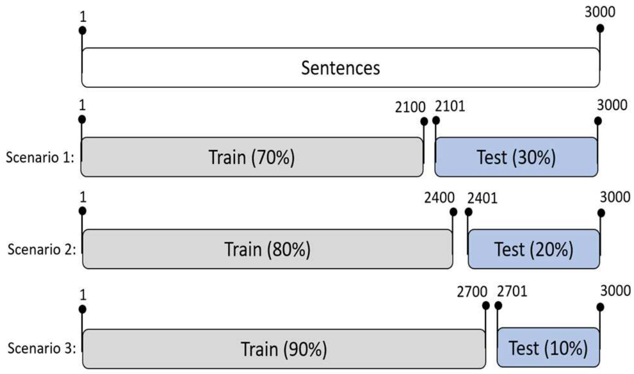


Fig. 3 Data Proportion Scenarios

D. Model Building

Neural Machine translation in this study uses the LSTM model with encoder-decoder. LSTM has been successfully applied in various NMT modeling as one of the RNN variants. An input gate, output gate, and forget gate are part of an LSTM unit. The input gate controls the model's input, the output gate controls the model's output, and the forget gate calculates the degree of memory module forgetting at the last moment.

In the LSTM architecture, as shown in Fig. 4, the front-end model encodes the input sequence into a context vector called an encoder. The first hidden layer was the embedding layer, and then the context vector was decoded verbatim by a back-end model called a decoder [14], [35]. The encoder computes a representation for each source sentence. Then the decoder generates sentence-by-sentence translations by treating the generated previous sentences as a global target context [36], [37]. Since the encoder and decoder are both iterative, they have loops that process each sequence part at a different time step.

The model is trained using Adam's efficient approach for stochastic gradient descent and minimizes the categorical loss function because the prediction problem is a multi-class classification problem [38]. Adam is more efficient and requires less memory and training time [39]. Then train the model with epochs varying from 100 to 1000 and batch size 64.

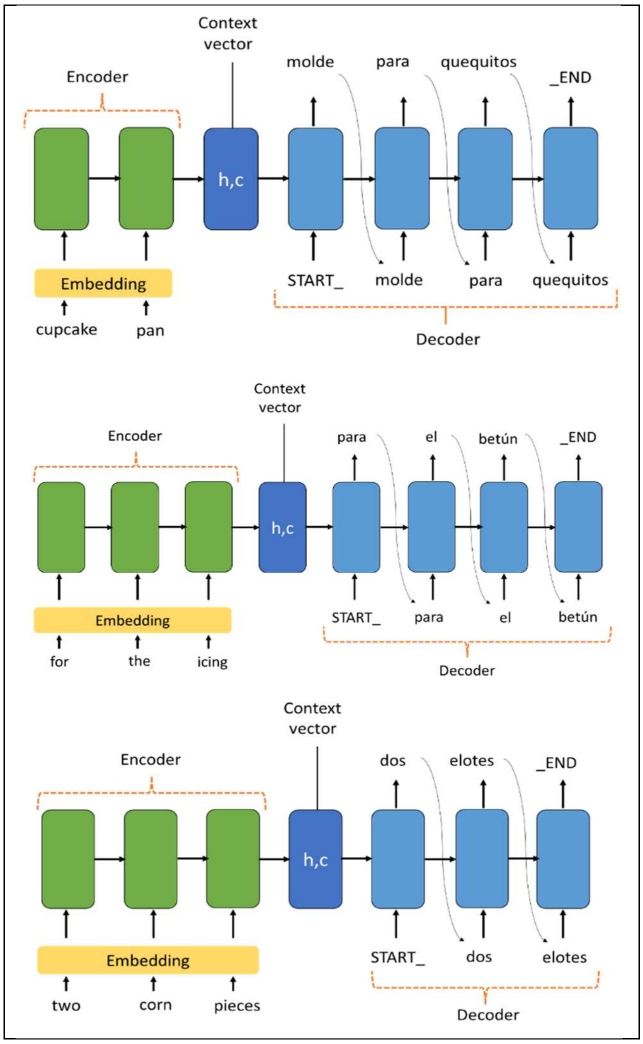


Fig. 4 LSTM Model

E. Evaluation

Evaluation in this study used the Bilingual Evaluation Understudy Score (BLEU) unigram to 4-gram [40]. BLEU evaluates the quality of a translation that a machine has translated from one natural language to another [41]. BLEU measures the modified n-gram precision score between the automatic and reference translations and uses the brevity penalty constant [42]. The BLEU value is obtained by multiplying the brevity penalty with the geometric mean of the modified precision score. The higher the BLEU value, the more accurate the reference is.

The value of BLEU is in the range of 0 to 1 [43]. A translation achieves a value of 1 if the translation is identical to the reference translation. Therefore, even with human translation, it is impossible to get a value of 1. It is essential to know that the more translations of references per sentence, the higher the value. To produce a high BLEU value, the length of the translated sentence must be close to the length of the reference sentence, and the translated sentence must have the same word and order as the reference sentence [44]. The writing of the BLEU formula can be seen in Eq. (1) to (3).

$$BP_{BLEU} = \begin{cases} 1 & if\ c > r \\ e^{\left(1-\frac{r}{c}\right)} & if\ c \leq r \end{cases} \quad (1)$$

$$P_n = \frac{\sum C\epsilon\ corpus\ n-gram\ \epsilon C \sum count\ clip^{(n-gram)}}{\sum C\epsilon\ corpus\ n-gram\ \epsilon C \sum count_{\ (n-gram)}} \quad (2)$$

$$\text{BLEU} = BP_{BLEU} \,.\, e^{\sum_{n-1}^{N} w_n \log p_n} \quad (3)$$

BP is brevity penalty, c is the word count of automatic translation results, r is the number of reference words, P_n is the modified precision score, w_n is 1/N (the standard N value for BLEU is 4), and p_n is the number of *n-grams* translated according to the reference divided by the number of *n-grams* translated.

III. Results and Discussion

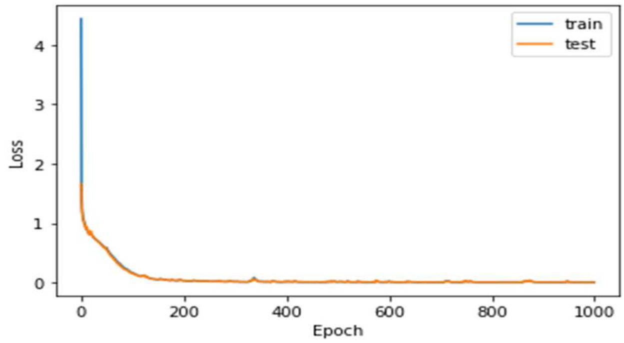
In this study, neural machine translation uses the LSTM encoder-decoder method with various input data scenarios. Two models are processed in this research: Model 1 Spanish to English and Model 2 English to Spanish. To find out the best available results, each model was tried using a variety of epochs from 100 to 1000. The results were compared using the resulting BLEU value at the end of the discussion.

A. Model 1 Spanish to English

Based on Table II, the larger the epoch used, the greater the value of BLEU 1, 2, and 3. Moreover, the longer the processing time required. The best BLEU value is at Epoch 1000 and 300, as shown in Fig. 5. The best BLEU value in Model 1 scenario 1 is at Epoch 1000 with 0.99842.

TABLE II
Comparison of BLEU results model 1 scenario 1

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.91256	0.84803	0.78517	0.65990	148
200	0.98365	0.95797	0.92255	0.85162	208
300	0.98736	0.96462	0.93852	**0.88828**	268
400	0.98923	0.97338	0.94563	0.88445	331
500	0.99009	0.95969	0.92608	0.85369	438
600	0.99025	0.96914	0.93707	0.87308	448
700	0.99226	0.97498	0.94268	0.88097	528
800	0.99234	0.97064	0.93972	0.87404	627
900	0.99355	0.96851	0.93715	0.87177	672
1000	**0.99842***	**0.97519**	**0.94648**	0.887266	687



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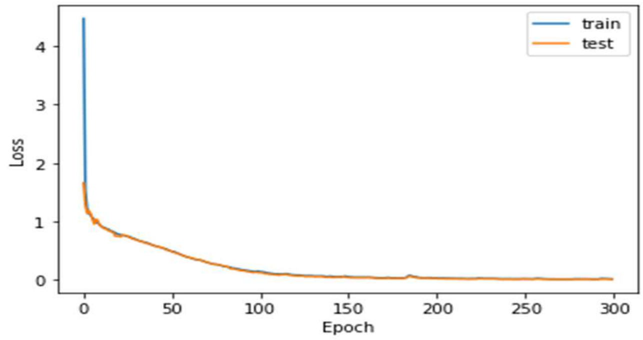


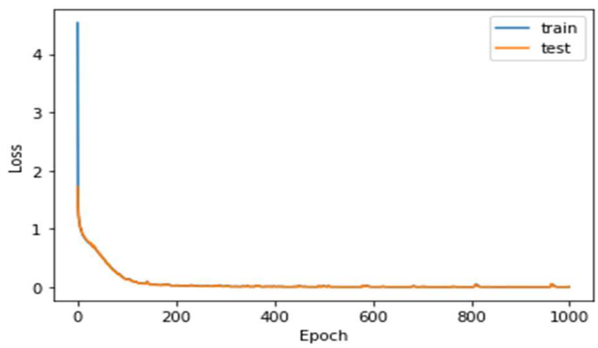
(b)

Fig. 5 Best Epoch Graphics Model 1 Scenario 1 (a) 1000 Epoch, (b) 300 Epoch

TABLE III
Comparison of BLEU results model 1 scenario 2

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.88563	0.79067	0.71104	0.56190	147
200	0.98433	0.95426	0.91348	0.83254	195
300	0.98638	0.95966	0.92664	0.85981	328
400	0.98699	0.96441	0.93401	0.86838	388
500	0.98717	0.96464	0.93874	0.87946	448
600	0.98974	0.96627	**0.95011**	**0.89198**	507
700	0.99189	0.96816	0.93482	0.86737	548
800	0.99370	0.97436	0.93732	0.86984	609
900	0.99533	0.97496	0.94140	0.87110	688
1000	**0.99609***	**0.97748**	0.94595	0.88732	748

From the results in Table III, the larger the epoch used, the greater the value of the majority of BLEU, especially BLEU 1 and BLEU 2. When entering Epoch 600, the value in BLEU 3 and 4 decreased and then rose again until the end of Epoch 1000. The bigger epoch, the longer the processing time needed is also getting longer. The best BLEU results in Model 1 Scenario 2 are at Epoch 1000 with a BLEU 1 value of 0.99609, which takes 748 seconds to process. The best BLEU value is at Epoch 1000 and 600, as shown in Fig. 6.



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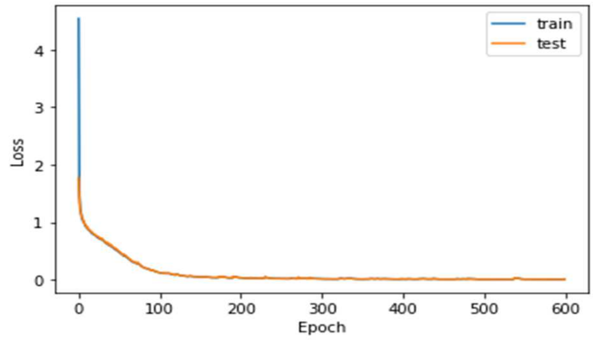


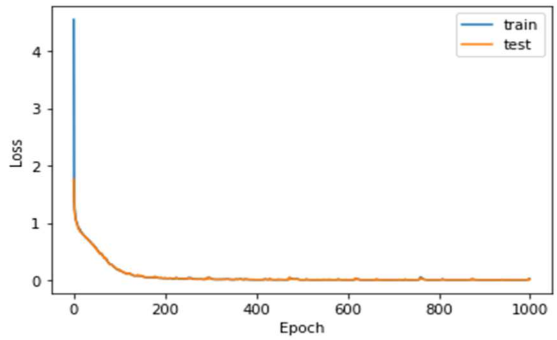
(b)

Fig. 6 Best Epoch Graphics Model 1 Scenario 2 (a) 1000 Epoch, (b) 600 Epoch

TABLE IV
COMPARISON OF BLEU RESULTS MODEL 1 SCENARIO 3

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.82346	0.72415	0.65001	0.50190	132
200	0.97554	0.94508	0.90648	0.83392	268
300	0.98861	0.96847	**0.94046**	**0.88104**	328
400	0.99055	0.96709	0.93610	0.87424	388
500	0.99159	0.97067	0.93853	0.87630	440
600	0.99004	0.96831	0.93826	0.87410	508
700	0.99035	0.96771	0.93395	0.86517	579
800	0.99155	0.96947	0.94043	0.87626	688
900	0.99170	0.96922	0.93935	0.87716	748
1000	**0.99195***	**0.96936**	0.94026	0.87834	807

Table IV shows that the larger the epoch used, the longer the processing time. When Epoch 100, the processing time only takes 132 seconds, but when the epoch increases to 1000, the processing time becomes longer by 807 seconds. In addition, the larger the epoch used, the greater the value of BLEU 1 and 2. The best BLEU on Model 1 Scenario 3 is 0.99195. The Epoch graph with the best BLEU value is at Epoch 1000 and 300, as shown in Fig. 7.



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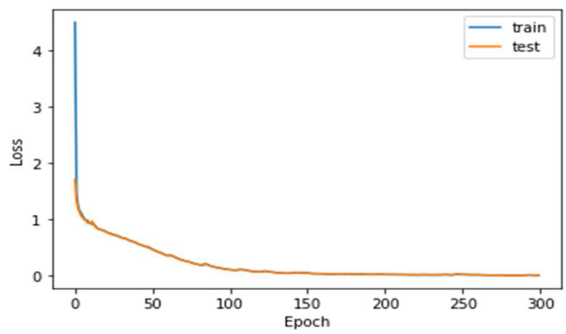


(b)

Fig. 7 Best Epoch Graphics Model 1 Scenario 3 (a) 1000 Epoch, (b) 300 Epoch

Based on Tables II to IV, for Model 1 Spanish to English, the BLEU value increases according to the size of the epoch used. The BLEU value always increases from all scenarios during Epoch 100–500. When entering an epoch above 500, several Scenarios experience a decrease in BLEU value but only a slight difference and increase again when using Epoch 1000. The best BLEU value is most of all Scenarios generated when BLEU 1. This happens because, one by one, the words that exist during processing are correctly interpreted according to the existing target. The best BLEU 1 value for Model 1 is in Scenario 1, with 70%:30% data sharing of 0.99842.

The processing time comparison between scenarios in Model 1 can be seen in Fig. 8. The larger the epoch used, the more time it takes to process it from all scenarios.

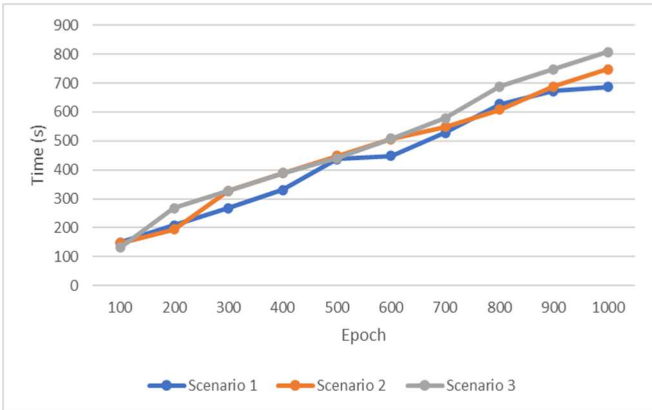


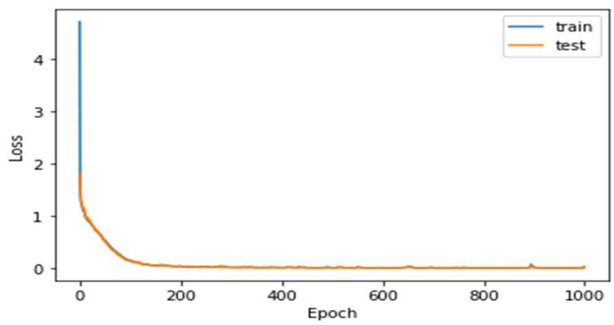
Fig. 8 Processing Time Comparison Graph of Model 1

B. *Model 2 English to Spanish*

Based on Table V, the larger the epoch used, the greater BLEU 1 and 2. Furthermore, the longer the processing time required. The best BLEU value is at Epoch 1000 and 700, as shown in Fig. 9. The best BLEU value in Model 2 scenario 1 is at Epoch 1000 with 0.99717.

TABLE V
COMPARISON OF BLEU RESULTS MODEL 2 SCENARIO 1

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.70150	0.57851	0.50491	0.36678	119
200	0.98374	0.97152	0.95358	0.91475	204
300	0.98418	0.96703	0.94634	0.89472	308
400	0.98690	0.97251	0.94992	0.90029	327
500	0.98861	0.96959	0.94736	0.89544	387
600	0.99158	0.97757	0.95792	0.91283	408
700	0.99342	0.98084	**0.96745**	**0.93052**	500
800	0.99573	0.98386	0.95874	0.91078	567
900	0.99701	0.97760	0.95259	0.89936	627
1000	**0.99717***	**0.98521**	0.96742	0.92480	639



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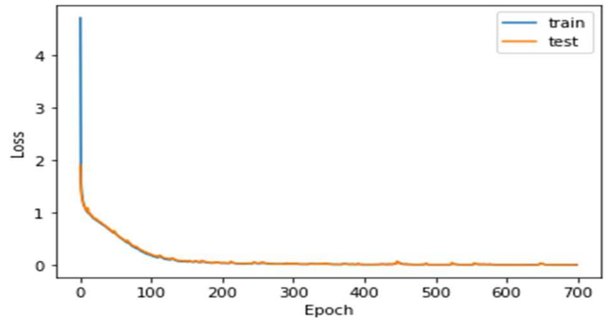


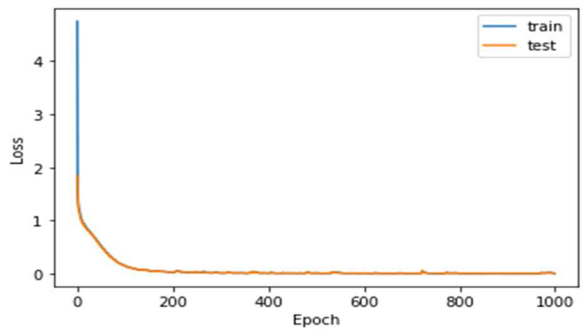
(b)

Fig. 9 Best Epoch Graphics Model 2 Scenario 1 (a) 1000 Epoch, (b) 700 Epoch

TABLE VI
COMPARISON OF BLEU RESULTS MODEL 2 SCENARIO 2

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.83987	0.74623	0.67589	0.53832	148
200	0.98759	0.96184	0.93277	0.87249	208
300	0.99045	**0.97651**	**0.95813**	**0.91361**	270
400	0.99073	0.97485	0.95364	0.90712	388
500	0.99117	0.97201	0.94807	0.89514	387
600	0.99113	0.97098	0.94423	0.88691	508
700	0.98950	0.96915	0.94900	0.89970	532
800	0.99040	0.97227	0.94839	0.89815	618
900	0.99167	0.97581	0.95642	0.90791	628
1000	**0.99179***	0.97190	0.94788	0.89691	747

From the results in Table VI, the larger the epoch used, the greater the value of the BLEU 1 majority. Epoch 500 to 700 decreases in value, and Epoch 800 rises again until Epoch 1000. Moreover, the more significant the epoch, the longer the processing time required. The best BLEU results in Model 2 Scenario 2 are at Epoch 1000 with a BLEU 1 value of 0.991790, which requires a processing time of 747 seconds. The Epoch graph with the best BLEU value is at Epoch 1000 (BLEU 1) and 300 (BLEU 2, 3, and 4), as shown in Fig. 10.



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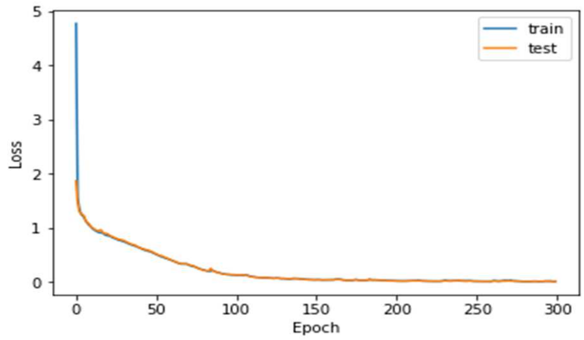


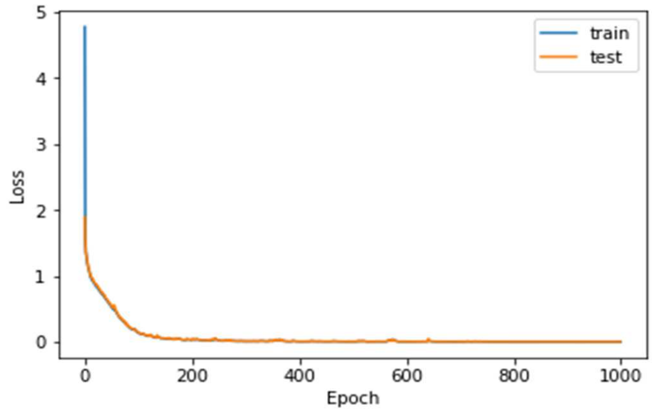
(b)

Fig. 10 Best Epoch Graphics Model 2 Scenario 2 (a) 1000 Epoch, (b) 300 Epoch

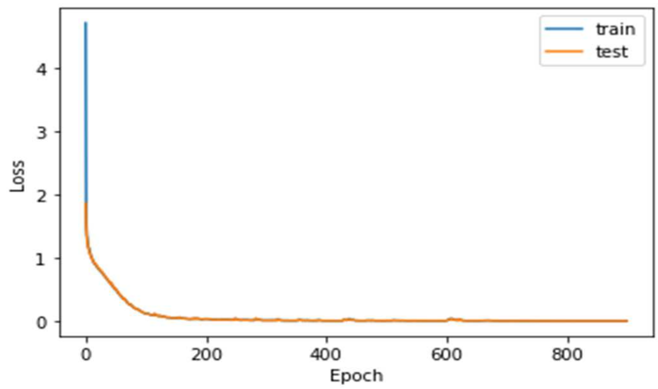
TABLE VII
COMPARISON OF BLEU RESULTS MODEL 2 SCENARIO 3

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4	Times (s)
100	0.85235	0.76845	0.70324	0.57220	130
200	0.97238	0.94603	0.92051	0.86058	213
300	0.98639	0.96816	0.94610	0.89514	328
400	0.98784	0.96871	0.94643	0.89591	387
500	0.98830	0.97202	0.95291	0.90764	448
600	0.98875	0.97111	0.95122	0.90483	508
700	0.99005	0.97292	0.95327	0.90776	568
800	0.98981	0.97290	0.95250	0.90675	618
900	0.99171	**0.97432**	**0.95344**	**0.90788**	747
1000	**0.99225***	0.97390	0.94925	0.89580	807

Table VII shows that the larger the epoch used, the longer the processing time. When Epoch 100, the processing time only takes 130 seconds, but when the epoch increases to 1000, the processing time becomes longer by 807 seconds. In addition, the larger the epoch used, the greater the value of BLEU 1. The best BLEU on Model 2 Scenario 3 is 0.99225. The Epoch chart with the best BLEU value is at Epoch 1000 and 900, as shown in Fig. 11.



(a)



(b)

Fig. 11 Best Epoch Graphics Model 2 Scenario 3 (a) 1000 Epoch, (b) 900 Epoch

Based on the current results, for Model 2 English to Spanish, the best BLEU value of most scenarios is generated during BLEU 1. The best BLEU 1 value is in Scenario 1 with 70%:30% data sharing, 0.99717. A comparison of processing time between scenarios in Model 2 can be seen in Fig. 12. The larger the epoch used, the more time it takes to process it from all scenarios.

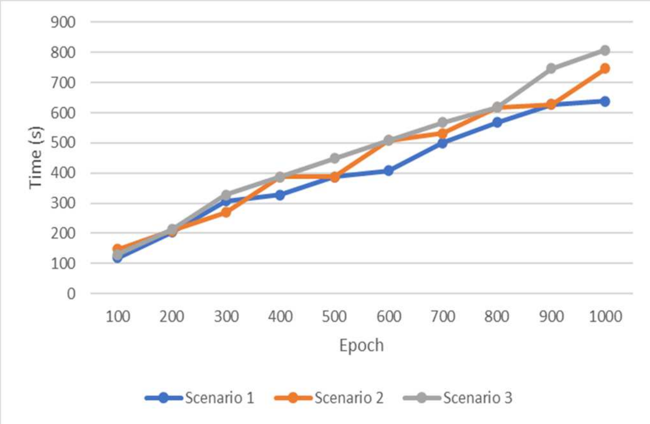


Fig. 12 Processing Time Comparison Graph of Model 2

From the overall results, it can be seen that Model 1 Spanish to English has a higher BLEU value when compared to Model 2 English to Spanish. The best BLEU value in Model 1 is 0.998426, while in Model 2, it is 0.997175. Of all scenarios, the BLEU value always increases during Epoch 100–500. When entering an epoch above 500, several Scenarios experience a decrease in BLEU value but only a slight difference and increase again when using Epoch 1000. A scenario with data sharing of 70%:30% has the best BLEU value for all existing models. The more training data used in this study, the lower the BLEU value of the three scenarios. In addition, the current processing time increases according to the epoch size. The best BLEU value of most scenarios is generated when BLEU 1. This happens because, one by one, the words that exist during processing are correctly interpreted according to the existing target.

IV. Conclusions

The LSTM method can translate food recipes from English to Spanish or vice versa from Spanish to English based on the research results. LSTM encoder-decoder succeeded in obtaining BLEU with the best value, namely when translating Spanish to English with 1000 epochs while using a 70%:30% data composition of 0.99842 with BLEU 1 because English was shorter than Spanish. Furthermore, one English word may have more than one Spanish translation, reducing the translation accuracy. For further research, researchers can use filtered data so that it only appears once and does not repeat itself in the dataset.

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