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Optimizing Indonesian-Sundanese Bilingual Translation with Adam-Based Neural Machine Translation

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Abstract

This research seeks to construct an automatic translation between Indonesian and Sundanese languages based on the Neural Machine Translation (NMT) method. The model used in this study is the Long Short-Term Memory (LSTM) type, which carries out an encoder-decoder structure model learned with Bible data. The text translation here was conducted in different epochs to optimize the process, followed by the Adam optimization algorithm. Testing the Adam optimizer with different epoch settings yields a BLEU score for Indonesian to Sundanese translations of 0.991785, higher than the performance of the None optimizer. Experimental results demonstrate that Indonesian to Sundanese translation using Adam optimization with 1000 epochs consistently performed better in BLEU - Bilingual Evaluation Understudy - scoring than Sundanese to Indonesian translation. Limitations of the research were also put forth, particularly technical issues related to the collection of data and the Sundanese language's complex grammatical features, that the model can only partially express, honorifics, and the problem of polysemy. Also, it must be mentioned that no special hyperparameter selection was performed, as parameters were chosen randomly. In future studies, transformer-based models can be investigated since these architectures will better deal with complex language via their self-attention mechanism.

Keywords: *Adam; BLEU; Indonesian; LSTM; Sundanese*

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1. Introduction

The Sundanese, or Sundatribe, people come from West Java Island, Indonesia, where some comprise the existing cultures, much of which is the Sundanese native culture that endeavors for a pro-nationalist education aimed at a better social organization [1]. West Java is one of the most populated provinces in Indonesia, with an estimated population of nearly 49 million as of 2022 data. Sundanese is the third in order of the most widely spoken languages in this country, with over thirty-two million speakers, ranking it 52nd among the most commonly spoken languages worldwide. It is used in West Java, Banten Province, and as a 'minority language' in some regions, including Jakarta, Lampung and Central Java [2]. The task is to translate Indonesian into regional languages. The first languages include Sundanese, where some parts of the language structure and culture are intricate. While the national language of Indonesia is based on an uncomplicated sentence structure, the Sundanese language entails a richer formal and dialect construction, verb conjunctions, and tenses based on the context of the speaker to the subject therein. Such differences play a very important role in how automated language translation systems function, which is not only based on what the words of a sentence mean but also on what tone and feeling a certain language holds. Such issues are polysemy, phraseological units, and so forth, which are present hierarchical speech norms closely intertwined within the Sundanese culture.

Sundanese translation research includes bidirectional translations of Indonesian into Sundanese and Sundanese into Indonesian languages [3], [4], [5], [6] as well as within the regional languages, including the Javanese language and other ethnic languages in Indonesia [7], [8], [9], [10]. However, to this day, this

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is the first study to our knowledge that uses the Bible dataset to translate Bahasa Indonesia into Bahasa Sunda and vice versa with the LSTM method, which is significant because it has substantial relevance to culture, history, and theology [11], [12]. The Bible was chosen for this research not only because it has wide and well-organized material but also because it has formal language and subtle meanings that make it suitable for developing models that can effectively address the linguistic complexities in Sundanese. Recent studies showed that none of them used an optimizer during the translation process.

Recent studies have shown that Adam optimization, as an adaptive gradient method, plays a crucial role in optimizing models such as LSTM within NMT contexts, particularly for languages with complex morphological and syntactic structures. Adam is known to effectively minimize categorical loss and is more efficient compared to standard optimization techniques like SGD (Stochastic Gradient Descent), providing more stability during model training [13], [14], [15], [16]. For instance, its application to bilingual and multilingual translation tasks has demonstrated improved accuracy and convergence rates in diverse contexts [17], [18], [19], [20]. This underscores the novelty and relevance of employing Adam optimization in this study, as it significantly enhances the capability of LSTM models to handle sequential data processing concerning the Sundanese language's rich cultural and structural features.

Cultural and religious aspects also increase their relevance in translation tasks since the NMT model can refrain from solely lexical approaches and address the distinct culture of the Sundanese communication context [16]. It has been observed that languages encoded in LSTM-based models are quite effective in understanding sequences due to their ability to capture contextual information via their recurrent design, which happens to be the case for the Sundanese language as well [13], [14], [15]. LSTM has, however, remained relevant in NMT, as modern systems have integrated transformer-based architectures capable of capturing long-range dependencies. However, LSTM's lower data needs and ability to sustain relevance over moderate lengths of sequences makes it ideal for NMT of smaller datasets, for instance, in Madura-Indonesian translation [19], [21]. The appropriate recurrent nature in NMT-based models and LSTM architecture features help Pet's engaging translation become effective since their supposed structural composition fits long dispatch connections that subtend theological pieces of the text [22], [23]. Challenges like honorifics and polysemy in Sundanese require advanced modeling, which has been the focus of LTSM models today, with some progress made through various optimization techniques [24], [25]. The importance of optimization in NMT frameworks is noticeable, particularly in NMT models augmented with a dynamic error-repair strategy, which is known to improve robustness in low-resource languages [22], [26], [27].

This research seeks to use an NMT approach that employs an LSTM model for translating biblical texts to address these issues. The Bible dataset was chosen as it seems to contain much text, which facilitates the learning of the NMT system and a variety of sentence constructions in diverse contexts. This capability enables the model to understand how the Indonesian and Sundanese languages' wordings and structuring differ and the cultures and religions in focus. This contrasts with previous relevant studies; this research intends not only to accomplish lexical translation but also to capture these subtleties. For such activities, the LSTM model, known to be strong in sequential data processing, is advisable for the task because it is good at handling temporal correlations among words, which is important in context and degree of respect in communication using the Sundanese language. In short, employing LSTM, this research proposes to improve the accuracy of the translation and the richness of the meaning to enhance the understanding of the Bible in both languages.

2. Research Methods

This research was conducted in four main stages: dataset collection, preprocessing, translation, and evaluation.

2.1 Dataset Collection

In the first stage, the researcher obtained data from the online Bible of 66 chapters. They Align the Indonesian and Sundanese verses using web scraping techniques and end up with a dataset as shown in Table 1, which shows the first three rows. Considering the wide disparity of languages, it was important to carry out a preprocessing stage to normalize the format.

Table 1. Dataset

Indonesian	Sundanese
1Setelah itu, Yusuf merebahkan diri pada wajah ayahnya dan menciumnya.	1Gabrug layon teh ku Yusup dirangkul, ditatangkeup ditangisan, rarayna digalentoran.
2Yusuf memerintahkan para pelayannya, yaitu para tabib, untuk merempah-rempahi jenazah ayahnya. Para tabib pun merempah-rempahi jenazah Yakub.	2Yusup marentahkeun tabib-tabib bawahanana, sina ngabalsem ramana.
3Dia memenuhinya selama 40 hari karena demikianlah waktu untuk merempah-rempahi jenazah, dan orang-orang Mesir menangisinya selama tujuh puluh hari.	3Lilana ngabalsem opat puluh poe, sakumaha biasana. Urang Mesir kabeh barela sungkawa meunang tujuh puluh poe.

2.2 Preprocessing

The second stage encompasses preprocessing, which involves both manual and Natural Language Processing (NLP) techniques, as illustrated in Figure 1.

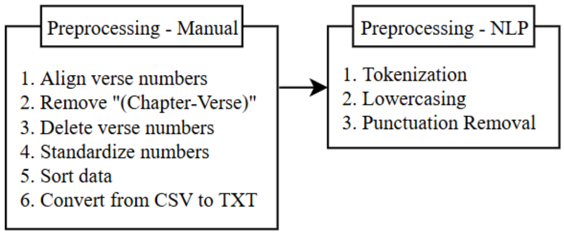

Figure 1. Preprocessing

The first stage of preprocessing is manual. The first step in manual preprocessing aims to equalize the number of verses in both languages, addressing the issue where some verses summarize others, leading to discrepancies that could negatively impact BLEU scores. Verses containing more than three sentences are split based on punctuation, while those with fewer than three sentences are merged to maintain structural integrity. The decision to use a three-sentence limit was made to optimize the process, as evidenced by the data presented in Table 2 and Table 3.

Table 2. Verse Splitting Sample

Before		After	
Indonesian	Sundanese	Indonesian	Sundanese
7Dari keturunan Benyamin: Salu, anak Mesulam, anak Hodawya, anak Hasenua,	7(9:7-8) Ti kaom Binyamin anu maratuhna di Yerusalem teh nya eta: Salu bin Mesulam bin Hodawia bin Hasenua. Yibneya bin Yeroham. Ela bin Usi bin Mikri. Mesulam bin Sepaca bin Rehuel bin Yibnia.	7Dari keturunan Benyamin: Salu, anak Mesulam, anak Hodawya, anak Hasenua,	7Ti kaom Binyamin anu maratuhna di Yerusalem teh nya eta: Salu bin Mesulam bin Hodawia bin Hasenua.
8Yibnea, anak Yeroham, Ela, anak Uzi, anak Mikhri, dan Mesulam, anak Sefaca, anak Rehuel, anak Yibnia.	8(9:7)	8Yibnea, anak Yeroham, Ela, anak Uzi, anak Mikhri, dan Mesulam, anak Sefaca, anak Rehuel, anak Yibnia.	8Yibneya bin Yeroham. Ela bin Usi bin Mikri. Mesulam bin Sepaca bin Rehuel bin Yibnia.

In Table 2, it is evident that sentences 7 and 8 in the Indonesian text are distinct. However, the Sundanese translation consolidates these two sentences into a single sentence, with sentence eight merely referencing sentence seven without contributing additional content. As a result, if sentence 8 in Indonesian contains a specific statement while the corresponding Sundanese sentence is void of content, the machine translation model may encounter challenges in addressing this gap, which can significantly diminish the BLEU score. This reasoning similarly applies to the merging of sentences. To enhance model performance and ensure a more coherent translation, we have decided to eliminate the practice of referencing previous verses in the Bible.

Table 3. Verse Merging Sample

Before		After	
Indonesian	Sundanese	Indonesian	Sundanese
17Kesombongan manusia akan ditundukkan; kemegahan manusia yang meninggi akan direndahkan, hanya TUHAN yang akan ditinggikan pada hari itu.	17(2:17-18) Katakaburan manusa bakal eureun, kaadigungan bakal dibasmi. Brahala-brahala bakal beak. Dina waktu eta ngan PANGERAN anu bakal diagungkeun.	17Kesombongan manusia akan ditundukkan; kemegahan manusia yang meninggi akan direndahkan, hanya TUHAN yang akan ditinggikan pada hari itu. Semua berhala akan lenyap.	17Katakaburan manusa bakal eureun, kaadigungan bakal dibasmi. Brahala-brahala bakal beak. Dina waktu eta ngan PANGERAN anu bakal diagungkeun.
18Semua berhala akan lenyap.	18(2:17)		

The second step involves the removal of the notation "(Chapter-Verse)." Within the context of the dataset, this notation is deemed irrelevant and can potentially interfere with the model's performance. Table 4 illustrates that "(Chapter-Verse)" placement is random, as it can appear after the verse number, in the middle of the text, or at the end. Given this inconsistency in placement, it is necessary to delete the file manually.

Table 4. "(Chapter-Verse)" Sample

Indonesian	Sundanese
13(13-12b) Semua orang-orang kudus mengirimkan salam untukmu.	13(13-12) Aya salam ti sakabeh umat Allah keur aranjeun.
14Aku berharap untuk menemuimu segera dan kita akan berbicara secara tatap muka. (1-15) Damai sejahtera bagimu. Kawan-kawan di sini mengirimkan salam untukmu. Sampaikan juga salam kami kepada setiap saudara di sana.	14engke bae ari pendak, margi sim kuring gaduh maksud enggal-enggal mendakan. (1-15) Mangga, wilujeng. Aya salam ti sadaya rerencangan di ditu. Kintun salam ka sadaya rerencangan di dieu.

The third step entails the removal of the verse number from the dataset. In the original dataset, verse numbers are affixed directly to the text without any spaces or separators. For instance, in verse 14 of the Book of Genesis in Indonesian, the text reads, "14200 ekor kambing betina dan 20 ekor kambing jantan, 200 ekor domba betina dan 20 ekor domba jantan," where "14200" appears without a separator; here, "14" represents the verse number, and "200" signifies the number of she-goats. Consequently, eliminating verse numbers necessitates a manual process of verification, wherein each verse must be checked individually.

The fourth step involves the standardization of numbers within the dataset. A notable discrepancy exists between numeric and cardinal numbers in both Indonesian and Sundanese, thereby necessitating a standardization process. As illustrated in Table 5, a specific rule is applied wherein cardinal numbers in Sundanese are preserved, while numeric numbers or any combination thereof are eliminated to enhance efficiency. The removal of these numeric representations does not compromise the meaning of the translation; rather, it serves the purpose of simplifying the translation results.

The fifth step involves sorting the dataset, which is conducted based on the number of available words [28]. In this process, sentences with the fewest words are positioned in the top row, while those with the highest word count are placed in the bottom row. This systematic arrangement facilitates a more organized dataset analysis and supports the subsequent processing stages.

The final step in the manual preprocessing phase involves converting the dataset format from CSV to TXT. The Indonesian and Sundanese datasets are delineated in the TXT format by a single tab. Furthermore, ensuring no trailing spaces at the end of each line is essential, as such spaces can lead to errors during the preprocessing stage utilizing NLP techniques and may adversely affect the BLEU scores. This attention to detail is critical for maintaining the integrity and accuracy of the translation process, as illustrated in Table 6.

Table 5. Number Standardization Sample

Before Indonesian	Sundanese	After Indonesian	Sundanese
Lalu sepuluh kakak Yusuf berangkat ke Mesir untuk membeli gandum	Bral sapuluh sadereksaderek Yusup arindit ka Mesir rek mareuli gandum	Lalu sepuluh kakak Yusuf berangkat ke Mesir untuk membeli gandum	Bral sapuluh sadereksaderek Yusup arindit ka Mesir rek mareuli gandum
Nuh berumur 600 tahun ketika air bah itu melanda bumi.	Dina waktu der caah, yuswa Enoh geus genep ratus taun.	Nuh berumur enam ratus tahun ketika air bah itu melanda bumi.	Dina waktu der caah, yuswa Enoh geus genep ratus taun.
Di dalam kastel Susan, orang Yahudi membunuh dan membinasakan lima ratus orang,	Di ibukota Susan wungkul, nu dipaehan ku urang Yahudi teh nepi ka aya 500 jelema.	Di dalam kastel Susan, orang Yahudi membunuh dan membinasakan orang,	Di ibukota Susan wungkul, nu dipaehan ku urang Yahudi teh nepi ka aya jelema.

Table 6. Dataset After Manual Preprocessing

Indonesian	Sundanese
Jangan membunuh.	Ulah maehan.
Jangan berzina.	Ulah ngaranyed.
Jangan mencuri.	Ulah maling.

Following the manual preprocessing phase, the second preprocessing stage is conducted using NLP, as detailed in Table 7. The raw sentences at this stage comprise the dataset that has undergone manual preprocessing. Tokenization is performed by segmenting sentences into tokens based on whitespace [29], facilitating subsequent text analysis. Lowercasing is applied to convert all words to lowercase for consistency across the dataset. Additionally, punctuation removal involves eliminating punctuation marks that are deemed irrelevant to the model's functioning [30]. Other potential techniques, such as Unicode normalization, were deemed unnecessary because the Bible dataset in both Sundanese and Indonesian already complies with ASCII standards. Furthermore, stemming, lemmatization, and stopword removal were intentionally excluded, as their application could lead to alterations in word meanings, which is vital for preserving the theological context inherent in Bible translations. The careful selection of these preprocessing steps has contributed to an enhancement in model performance, as evidenced by the observed improvements in BLEU scores.

Table 7. NLP Preprocessing

Step	Example Sentences
Raw Sentence	Umur Ishak adalah tahun.
Tokenization	[“Umur,”, “Ishak”, “adalah”, “tahun.”]
Lowercasing	[“umur,”, “ishak”, “adalah”, “tahun.”]
Punctuation Removal	[“umur,”, “ishak”, “adalah”, “tahun”]

2.3. *Translation Process*

Machine translation refers to the automatic transformation of a language into a different language without manual work [31]. In the current research, however, it is argued that LSTM networks are more valuable and practical than machine translations since they focus on translating phrases rather than individual words [11], [32]. In contrast to SMT, the translation process is more accurate because the context is integrated into the translation [33], [34]. Meanwhile, LSTM networks also take input sentences instead of words, improving the overall efficiency and prediction of NMT systems.

NMT has considerably improved over the traditional statistical models, achieving higher efficiency and accuracy during translations [35], [36]. The authors use LSTM with an encoder-decoder architecture for NMT, which has proved to be effective in different NMT tasks as a type of RNN [11], [28], [35]. An LSTM encoder can encode the input sequence and store relevant information in memory, which is then sent to the decoder via a Repeat Vector [34]. This memory is then used by the LSTM decoder, which sequentially outputs the target language as a sequence of words starting from the first word [37]. The model has a Time Distributed Dense layer that predicts the next word produced at each sequence step.

Each LSTM layer comprises 128 units and a 0.2 dropout rate to prevent an overfitting problem. It has been shown that 128 units are necessary to learn sequential data patterns sufficiently. Increasing the number of units provides a broader range of information but also at a higher cost in computation and the chances of overfitting, meaning that a proper model complexity to performance trade-off must be maintained.

The model has been trained for bi-lingual translation between Indonesian and Sundanese for None and Adam optimizers at 100, 500, 1000, 1500, and 2000 epochs. We also made use of early stopping to prevent overfitting. The Adam optimizer was chosen in this case, as it has been reported as an acceptable option for multiclass classification since it minimizes categorical loss more effectively and is less memory-intensive than SGD [19], [28]. Early stopping works by monitoring the validation loss, and if no decrease in the loss is observably improved for about 20 successive epochs, then the training is stopped. This strategy avoids overtraining, helps in resource optimization, and ensures that training stops when little or no further gains in the validation loss can be expected. This method improves the generalization ability of a model; wide parameters for patient setting may, however, cause early training to stop, reducing model effectiveness.

2.4 Evaluation

For generating scores, machine-translated output is consistently compared to reference translation using a BLEU matrix, which accounts for output length differences [38]. In this paper, quad grams help calculate the BLEU score and show the ratio of n-grams in the translation of the model found in the reference translations. A disadvantage in constructing the BLEU score should be that a very competitive translation would give too short outputs as the study tries to yield a score for translation length [39], [40]. BLEU scores span from 0 to 1, with a score of 1 signifying exceptional translation accuracy. In addition to quad grams, BLEU assesses unigrams, bigrams, and trigrams, where higher scores indicate closer alignment between machine output and human reference translations [41], [42]. In the program code, both the original sentence (target) and the translated results are organized within actual and predicted lists, each segmented into individual words, following the approach outlined in Equations 1 to 3.

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

$$P_n = \frac{Number\ of\ result\ and\ reference\ n\text{−}grams\ match}{Total\ number\ of\ translated\ n\text{−}grams} \quad (2)$$

$$BLEU = BP_{BLEU} \times exp(\textstyle\sum_{n=1}^{N} w_n \cdot log\ P_n) \quad (3)$$

The Brevity Penalty (BP) is applied when the translation output is shorter than the reference, serving as a corrective factor to discourage excessively concise translations. The variable c represents the word count in the machine-generated translation, while r denotes the word count in the reference translation. The metric P_n Quantifies n-gram precision by measuring how much the n-grams in the machine translation align with those in the reference text. Additionally, w_n represents the weight assigned to each n-gram, generally distributed equally across all n-grams to ensure balanced scoring.

3. Results and Discussions

The translation results based on the Bible dataset encompass two primary processes: translation from Indonesian to Sundanese and from Sundanese to Indonesian. Tables 8 and 10 present the BLEU scores achieved without applying any optimization, whereas Tables 9 and 11 display the BLEU scores obtained when Adam's optimization is utilized. The number of epochs varies across these tables due to early stopping, which ensures training halts upon reaching optimal performance without further improvement.

As shown in Table 8, the highest BLEU score was achieved in scenario 4, with an average BLEU of 0.987827, while the shortest processing time of 51 seconds was observed in scenario 1. A balanced performance between translation quality and processing efficiency is observed in scenario 3, which achieved an average BLEU score of 0.980502 with a processing time of 442 seconds. This scenario demonstrates near-peak BLEU performance with significantly reduced time requirements compared to higher epoch configurations.

The similarity in BLEU performance between Table 8 and Table 9 can be attributed to the characteristics of the dataset and the specific challenges of bilingual translation from Indonesian to Sundanese. This aligns with the patterns observed in Figure 5, where the complexity of linguistic features, such as polysemy and sentence structure variations, further underscores the nuanced nature of the task.

Table 8. None Optimization BLEU Results Indonesian to Sundanese

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4
100	0.234459	0.163284	0.163611	0.116964
500	0.819024	0.746834	0.711244	0.625283
1,000	0.987596	0.983566	0.980998	0.969846
1,500	0.991622	0.989795	0.988813	0.981078
1,745	0.991784	0.989846	0.988543	0.980526

Table 9. Adam Optimization BLEU Results Indonesian to Sundanese

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4
100	0.279367	0.190809	0.184816	0.130223
500	0.918524	0.880216	0.857178	0.801086
1,000	0.991785	0.989816	0.988584	0.980463
1,259	0.991779	0.989691	0.988438	0.980873
1,411	0.990977	0.988830	0.987675	0.979923

In Table 9, the optimal BLEU score is achieved in scenario 4, with an average value of 0.987695, while scenario 1 demonstrates the shortest processing time at 62 seconds. The most effective balance of translation quality and time efficiency is evident in scenario 3, where an average BLEU score of 0.987662 is reached with a processing time of 455 seconds. This scenario provides excellent BLEU performance, maintaining relatively fast processing speeds and values close to the optimal, demonstrating an efficient translation configuration.

The comparison between Table 8 and Table 9 reveals that both tables achieve their highest BLEU scores in scenario 3. While Adam Optimization requires slightly more processing time than None Optimization, it yields marginally higher BLEU values. As illustrated in Figure 2, Adam Optimization demonstrates a more stable and consistent trend in BLEU improvement as the epoch count increases. Consequently, when balancing translation quality with time efficiency, Adam Optimization at 1,000 epochs emerges as the most effective choice, providing an optimal balance between these critical factors.

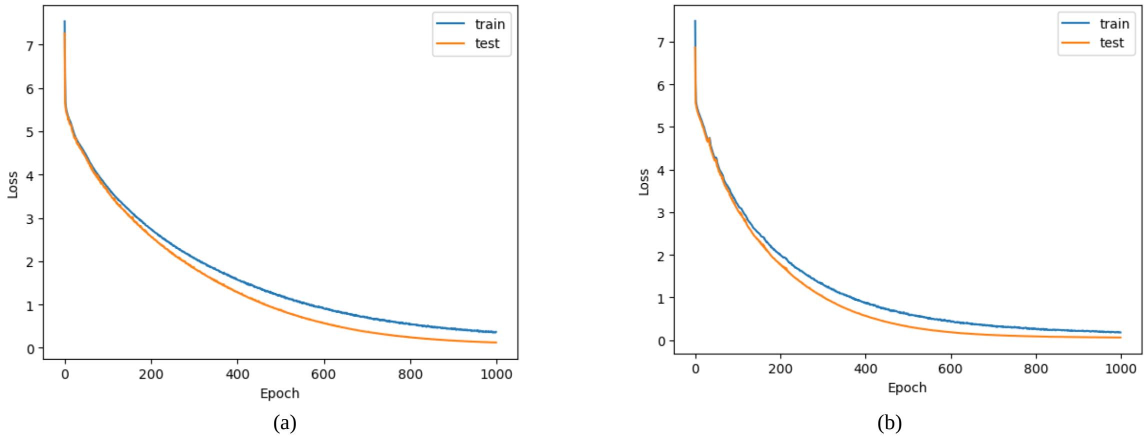

Figure 2. BLEU Results Graph Indonesian to Sundanese (a) None; (b) Adam Optimization

Table 10. None Optimization BLEU Results Sundanese to Indonesian

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4
100	0.148393	0.079876	0.066837	0.033701
500	0.479477	0.341669	0.294234	0.204953
1,000	0.821533	0.743369	0.698273	0.611488
1,500	0.892887	0.843888	0.816495	0.757962
2,000	0.938299	0.917433	0.906754	0.880339

In Table 10, scenario 5 achieves the highest average BLEU score of 0.910706, albeit with the longest processing time of 2.284 seconds. Scenario 4, however, offers nearly comparable BLEU results, with an average score of 0.827808 and a more efficient processing time of 1.675 seconds. Although scenario five yields the best BLEU score, scenario 4 demonstrates a more favorable balance between translation quality and processing time, making it a more practical choice.

In Table 11, scenario 5 achieves the highest BLEU value, with an average score of 0.935584; however, it necessitates a relatively long processing time of 1.993 seconds. In contrast, scenario 3 presents an impressive BLEU value, with an average of 0.877919 and a shorter processing time of 1.136 seconds. When evaluating time efficiency, scenario 3 utilizing Adam Optimization demonstrates superior results compared to scenario 5, positioning it as a more optimal choice for achieving an effective balance between translation quality and processing time.

Table 11. Adam Optimization BLEU Results Sundanese to Indonesian

Epoch	BLEU 1	BLEU 2	BLEU 3	BLEU 4
100	0.108170	0.048945	0.039539	0.000000
500	0.775290	0.674705	0.620880	0.518164
1,000	0.921051	0.889528	0.871228	0.829870
1,500	0.948661	0.933157	0.925740	0.904917
1,800	0.953058	0.939457	0.933688	0.916132

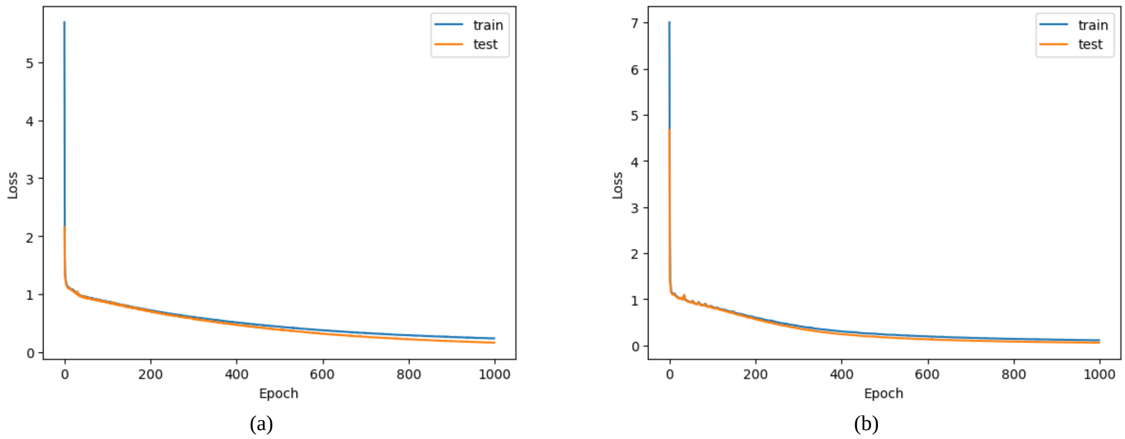

Figure 3. BLEU Results Graph Sundanese to Indonesian (a) None; (b) Adam Optimization

The analysis of the results presented in Table 10 and Table 11 indicates that scenario 3, which employs Adam Optimization, is the most suitable option for translating from Sundanese to Indonesian. While scenario 5, utilizing None Optimization, achieves the highest BLEU value, its processing time renders it less efficient in practical applications. In contrast, scenario 3 with Adam Optimization provides a commendable BLEU value and demonstrates superior processing efficiency. The graphical representation in Figure 3 illustrates that Adam Optimization at epoch 1,000 delivers the optimal balance between translation quality and processing time efficiency.

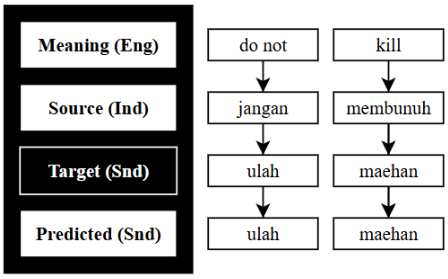

Figure 4. Ideal Output - Indonesian to Sundanese

Output can be ideal when the source, target, and prediction are identical [43], [44]. Achieving an ideal result in machine translation represents the primary objective of this endeavor. In the context of an online Sundanese dictionary, it is anticipated that each word in both Sundanese and Indonesian will have a 100% equivalent translation produced by the model, consequently leading to a high BLEU score. The ideal output samples demonstrating this equivalence from Indonesian to Sundanese and vice versa are illustrated in Figures 4 and 5, respectively.

Figure 4 illustrates the ideal output derived from the first row of the Indonesian to Sundanese dataset. In this instance, the target and predicted outputs generated by the machine translation are identical. The results of the machine translation demonstrate perfect concordance with the online Sundanese dictionary, wherein the Indonesian words "jangan" and "membunuh" are accurately translated on a word-for-word basis into "ulah" and "maehan" in Sundanese. This indicates that the machine translation effectively captures the literal meaning of phrases without any semantic deviation.

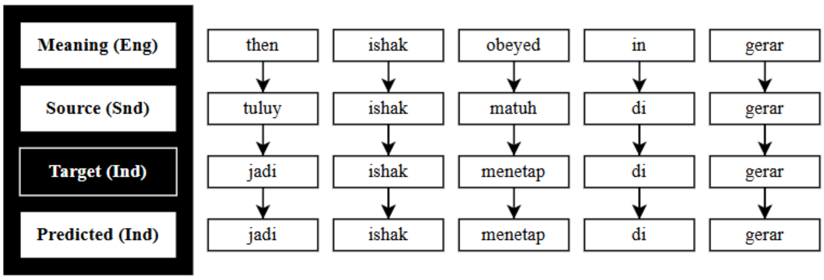

Figure 5. Ideal Output - Sundanese to Indonesian

The ideal output from the 1,250th row of the Sundanese to Indonesian dataset is presented in Figure 5. In this instance, both the target and predicted outputs are identical. However, a comparison with an online Sundanese dictionary reveals some differences in lexical interpretation. The Sundanese words "tuluy," "ishak," "matuh," "di," and "gerar" are translated into Indonesian as "lalu," "ishak," "subjek," "di," and "gerar," respectively, according to the online dictionary. Notably, the word "tuluy" is rendered as "maka" in Indonesian, while the machine translation predicts it as "jadi," which conveys a similar meaning, indicating polysemy. Additionally, a discrepancy is observed with the word "matuh," which should be translated as "menetap." However, the online Sundanese dictionary incorrectly translates it as "subjek," leading to a more significant divergence in meaning.

The primary distinction between the ideal outputs of Indonesian and Sundanese and vice versa resides in the consistency of capturing literal meanings. The translation from Indonesian to Sundanese aligns more closely with online dictionaries, whereas the translation from Sundanese to Indonesian exhibits lexical variations, albeit remaining semantically accurate.

Researchers certainly aspire to achieve ideal outputs. However, in practice, attaining such results is not always straightforward. Given the various scenarios explored, several outputs do not meet expectations, as illustrated in Figure 6 and Figure 7.

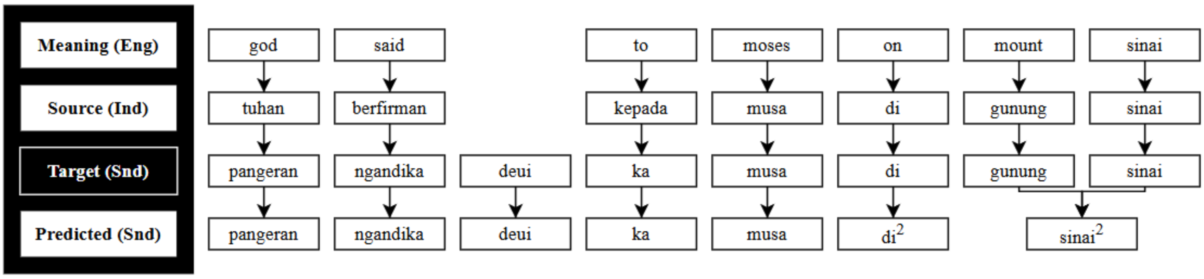

Figure 6. Nonideal Output - Indonesian to Sundanese

Figure 6 illustrates a non-ideal output sample from the 257th row of the Indonesian to Sundanese dataset. In this example, the word "deui" appears in both the target and predicted Sundanese sentences. Furthermore, there is a repetition of the words "di" and "sinai" in the prediction sentence, resulting in the phrase "gunung sinai" in the source and target sentences being rendered as "sinai sinai" in the prediction results. Notably, the word "gunung" is omitted in the Sundanese predictions, appearing only as "sinai sinai." When the Indonesian phrase consisting of the words “tuhan,” “berfirman,” “kepada,” “musa,” “di,” “gunung,” and “sinai” is translated word by word using an online Sundanese dictionary, it respectively translates to "déwa," “nyebutkeun,” “pikeun,” “mosa,” “dina,” “gunung,” and “sinai.” The usage of "pangeran" for "tuhan" and "ngandika" for "berfirman" highlights instances of polysemy. Additionally, the online Sundanese dictionary does not incorporate the word "deui," which indicates that the machine translation exhibits characteristics more aligned with colloquial Sundanese than with standard dictionaries, thereby offering a unique perspective in the translation results. However, this characteristic may negatively impact the BLEU score. The appropriate translation for this output should be “pangeran ngandika deui ka musa di gunung sinai.”

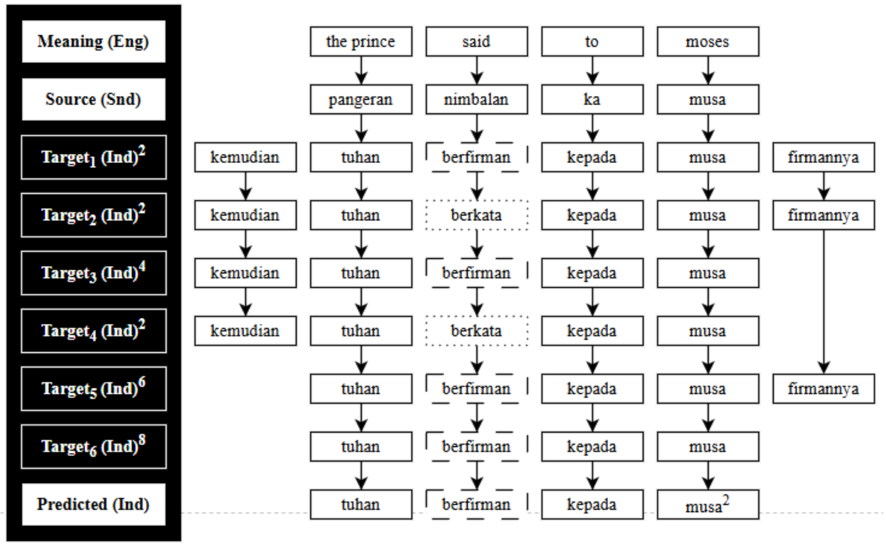

Figure 7. Nonideal Output - Sundanese to Indonesian

Figure 7 presents an example of non-ideal output due to multiple target translations, which introduces polysemy and causes a significant reduction in the BLEU score. In this instance, a single sentence in Sundanese is rendered into six Indonesian variations, with substantial differences appearing 24 times across the versions. Notably, the word "kemudian," which does not appear in the Sundanese source sentence, is used 10 times in the Indonesian target. Additionally, the Sundanese term "nimbalan" is translated into two different Indonesian words: "berfirman," which appears 20 times, and "berkata," appearing 4 times—both terms have similar meanings, reflecting polysemy. Furthermore, the phrase "firmannya," absent in the Sundanese source, appears 10 times in the Indonesian target. A comparison with an online Sundanese dictionary shows that the words “pangeran,” “nimbalan,” “ka,” and “musa,” when translated word-for-word into Indonesian, become “pangeran,” “berbicara,” “ke,” and “musa,” respectively. Meanwhile, the machine-generated sentence "tuhan berfirman kepada musa musa" includes unnecessary repetitions, indicating imperfections in the translation model’s parameters. The correct translation should be “tuhan berfirman kepada Musa,” capturing the intended meaning without redundant phrasing.

Overall, the results show that translations from Indonesian to Sundanese have a relatively higher BLEU score and a faster time taken when compared to Sundanese to Indonesian translation. This difference could be explained by the fact that there are intricate details in UP3, such as the prevalence of multiple-meaning words and the presence of honorifics, which detrimentally affect translation results. In particular, there is Report 21, where these words are used with multiple meanings, which is specific for polysemy in Sundanese. For instance, “Di taman, seueur kembang nu mekar” translates to “In the garden, many kembang flowers are blooming.” This describes a view of nature; in this case, kembang, meaning bisa, means flower. Another example is the expression “Acara ulang taun eta kembang pisan,” meaning “That birthday party was very kembang.” in this context, kembang means joyful, lively, and celebrative.

Furthermore, in Sundanese, language is not freely used. However, some should be considered in the hierarchy since language is a medium that determines the relationship between people and language, and honorifics mean important respect in communication. For example, the words 'Sami-sami, mugia Gusti Allah salawasna ngaberkahan urang’ are courteous, stating: 'Likewise, may God always bless us' where people are extending a polite wish. Words like ‘Gusti’ require the tone above as they are contextual, demonstrating the Stratification of Sundanese speech levels, which requires respective discipline regarding the language of address to respect social relations. In the dataset sample, those particular problems are present in Bible translations, where polysemous words used in the text with honorifics must be properly translated into one form or another. These are the paradigms where LMSM’s performance tends to be relatively poor, and this form of cultural courtesy deeply embedded in the Sundanese language may not have such default connections with the Indonesian, leading to translations where important cultural details are not correctly aligned.

As a result, there were shortcomings, such as word repetition and semantic divergences firing back to the model. Dataset imbalance, where a small number of phrases or word patterns can recur many times, is a contributing factor, as this causes the model to learn and rely heavily on such structures, producing repetitive translations. The LSTM setup may also have an incapacity to fathom such higher-order contexts, and especially in situations of polysemy where many valid translations exist, languages such as Indonesian would translate a single Sundanese keyword, thus affecting the Bleus score. While it should be noted that the model performs to boost the primary interpretations of phrases very well, other tasks such as conveying idioms or other more generalized tasks fail, which can be due to data scarcity in the training set or segmentation complexity of Sundanese grammar and sentence structure compared to Indonesian.

Adam Optimization models boast of stable and efficient performance, especially at higher epochs, meaning this would be effective in practice, yet advancements could still be made. Instead, better-balanced datasets or models such as transformers capable of understanding context better should be used, as Sundanese has linguistic complexities that require more finesse in creating frameworks.

Further assessment was made through another comparative study against the SGD optimizer to enhance the analysis of Adam's performance but at the optimal epoch. The results, as presented in Table 12, showed that Adam could arrive at higher BLEU scores than SGD in both translations. It is seen that while SGD had a shorter computation time, it performed poorly in translation accuracy and obtained drastically lower BLEU scores. Adam achieved higher BLEU scores and had a much better linguistic representation, particularly in capturing polysemy and using honorific language. This comparison of Adam in performing bilingual Indonesian-Sundanese translation is a reminder of the language's complexities and tasks.

Table 12. Adam and SGD Optimization BLEU Results Indonesian to Sundanese

Translation Direction	Optimizer	Time (s)	BLEU 1	BLEU 2	BLEU 3	BLEU 4
Indonesian to Sundanese	Adam	463	0.990946	0.988737	0.987501	0.979173
	SGD	362	0.080223	0.007889	0.000000	0.000000
Sundanese to Indonesian	Adam	1,146	0.927826	0.899068	0.887191	0.845857
	SGD	1,121	0.000000	0.000000	0.000000	0.000000

Adam's advanced optimization approach is the most effective choice for this translation task, achieving high accuracy and robustness in managing linguistic subtleties. In contrast, SGD's simpler gradient descent approach appears insufficient for addressing the intricate demands of Indonesian-Sundanese translation, further reinforcing Adam's suitability in this context.

In regards to the language selection this research is in the early stages. However, once it is related to the uses of Adam optimization, the results clearly show that Adam optimization can be used to improve the bidirectional translation in Indonesian Sundanese. Further research should be conducted in the future for better translation performances.

4. Conclusions

Following research findings, the LSTM method made it possible to easily translate the Bible from Indonesian to Sundanese and vice versa, with a better score coming from the Indonesian to Sundanese translation as evidenced by the higher BLEU values and quicker processing time. The Adam optimization with higher epochs helped offer better stability and performance across both translation directions. However, critical constraints are present in the LSTM models, particularly in its ability to handle long-paired or complicated language texts. LSTM models frequently face difficulties in fully understanding context, including the meaning behind words, leaving potential problems like word corners, semantic divergences, and issues relating to polysemy unaddressed. These problems are more extreme in Sudanese to Indonesian translation in that the grammatical sophistication and the lexico-semantics of Sundanese languages render it polysemous and hard to translate precisely. In addition, hyperparameter tuning was conducted without particular settings, which might have placed limits on what could have been gained in terms of performance. As such, these limitations indicate that, while LSTM hoses can grasp finely word-for-word meanings, larger, more abstract, or idiomatic types of expression are lost in processing. Future studies may benefit from the relatively new approach of a more context-sensitive model, the transformers, which may greatly improve the outcomes as their self-attention mechanisms improve contextual understanding. In addition, establishing guidelines such as Named Entity Recognition (NER) and more targeted hyperparameter optimization could also enhance the level of translation and efficiency of this study in place of the several limitations pointed out.

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References

[1] R. Yoseptry, "The Management of Sundanese Cultural Local Wisdom Learning in developing Early Childhood Nationalist

Character," *AL-ISHLAH J. Pendidik.*, vol. 14, no. 4, pp. 5035–5050, Sep. 2022, doi: 10.35445/alishlah.v14i4.1732.

[2] W. Wongso, H. Lucky, and D. Suhartono, "Pre-trained transformer-based language models for Sundanese," *J. Big Data*, vol. 9, no. 1, p. 39, Dec. 2022, doi: 10.1186/s40537-022-00590-7.

[3] Y. Heryadi, B. D. Wijanarko, D. Fitria Murad, C. Tho, and K. Hashimoto, "Indonesian-Sundanese Language Machine Translation using Bidirectional Long Short-term Memory Model," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia: IEEE, Feb. 2023, pp. 945–950. doi: 10.1109/ICCoSITE57641.2023.10127691.

[4] B. D. Wijanarko, Y. Heryadi, D. F. Murad, C. Tho, and K. Hashimoto, "Recurrent Neural Network-based Models as Bahasa Indonesia-Sundanese Language Neural Machine Translator," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia: IEEE, Feb. 2023, pp. 951–956. doi: 10.1109/ICCoSITE57641.2023.10127817.

[5] Y. Heryadi, B. D. Wijanarko, D. F. Murad, C. Tho, and K. Hashimoto, "Neural Machine Translation Approach for Low-resource Languages using Long Short-term Memory Model," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia: IEEE, Feb. 2023, pp. 939–944. doi: 10.1109/ICCoSITE57641.2023.10127724.

[6] B. D. Wijanarko, D. Fitria Murad, Y. Heryadi, C. Tho, and K. Hashimoto, "Exploring the Effect of Activation Function on Transformer Model Performance for Official Announcement Translator from Indonesian to Sundanese Languages," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia: IEEE, Feb. 2023, pp. 827–831. doi: 10.1109/ICCoSITE57641.2023.10127770.

[7] K. Azizah and M. Adriani, "Hierarchical Transfer Learning for Text-to-Speech in Indonesian, Javanese, and Sundanese Languages," in *2020 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, Depok, Indonesia: IEEE, Oct. 2020, pp. 421–428. doi: 10.1109/ICACSIS51025.2020.9263086.

[8] K. Resiandi, Y. Murakami, and A. H. Nasution, "Neural Network-Based Bilingual Lexicon Induction for Indonesian Ethnic Languages," *Appl. Sci.*, vol. 13, no. 15, p. 8666, Jul. 2023, doi: 10.3390/app13158666.

[9] R. Dabre, C. Chu, and A. Kunchukuttan, "A Survey of Multilingual Neural Machine Translation," *ACM Comput. Surv.*, vol. 53, no. 5, pp. 1–38, Sep. 2021, doi: 10.1145/3406095.

[10] S. Ranathunga, E.-S. A. Lee, M. Prifti Skenduli, R. Shekhar, M. Alam, and R. Kaur, "Neural Machine Translation for Low-resource Languages: A Survey," *ACM Comput. Surv.*, vol. 55, no. 11, pp. 1–37, Nov. 2023, doi: 10.1145/3567592.

[11] Z. Tan *et al.*, "Neural machine translation: A review of methods, resources, and tools," *AI Open*, vol. 1, pp. 5–21, 2020, doi: 10.1016/j.aiopen.2020.11.001.

[12] F. Stahlberg, "Neural Machine Translation: A Review," *J. Artif. Intell. Res.*, vol. 69, pp. 343–418, Oct. 2020, doi: 10.1613/jair.1.12007.

[13] X. Zheng *et al.*, "Adaptive Nearest Neighbor Machine Translation," in *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, Online: Association for Computational Linguistics, 2021, pp. 368–374. doi: 10.18653/v1/2021.acl-short.47.

[14] B. Zhang, D. Xiong, and J. Su, "Neural Machine Translation with Deep Attention," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 1, pp. 154–163, Jan. 2020, doi: 10.1109/TPAMI.2018.2876404.

[15] G. Ramesh *et al.*, "*Samanantar*: The Largest Publicly Available Parallel Corpora Collection for 11 Indic Languages," *Trans. Assoc. Comput. Linguist.*, vol. 10, pp. 145–162, Feb. 2022, doi: 10.1162/tacl_a_00452.

[16] H. Wang, H. Wu, Z. He, L. Huang, and K. W. Church, "Progress in Machine Translation," *Engineering*, vol. 18, pp. 143–153, Nov. 2022, doi: 10.1016/j.eng.2021.03.023.

[17] C. Lalrempuii and B. Soni, "Attention-Based English to Mizo Neural Machine Translation," in *Machine Learning, Image Processing, Network Security and Data Sciences*, vol. 1241, A. Bhattacharjee, S. Kr. Borgohain, B. Soni, G. Verma, and X.-Z. Gao, Eds., in Communications in Computer and Information Science, vol. 1241. , Singapore: Springer Singapore, 2020, pp. 193–203. doi: 10.1007/978-981-15-6318-8_17.

[18] F. A. Ahda, A. P. Wibawa, D. Dwi Prasetya, and D. Arbian Sulistyo, "Comparison of Adam Optimization and RMS prop in Minangkabau-Indonesian Bidirectional Translation with Neural Machine Translation," *JOIV Int. J. Inform. Vis.*, vol. 8, no. 1, p. 231, Mar. 2024, doi: 10.62527/joiv.8.1.1818.

[19] D. A. Sulistyo, "LSTM-Based Machine Translation for Madurese-Indonesian," *J. Appl. Data Sci.*, vol. 4, no. 3, pp. 189–199, Sep. 2023, doi: 10.47738/jads.v4i3.113.

[20] R. Ratawa and P. Nanda, "Artificial neural networks based damage severity assessment of structures using modal analysis," in *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022*, D. Zonta, Z. Su, and B. Glisic, Eds., Long Beach, United States: SPIE, Apr. 2022, p. 36. doi: 10.1117/12.2616710.

[21] B. Eikema and W. Aziz, "Is MAP Decoding All You Need? The Inadequacy of the Mode in Neural Machine Translation," in *Proceedings of the 28th International Conference on Computational Linguistics*, Barcelona, Spain (Online): International Committee on Computational Linguistics, 2020, pp. 4506–4520. doi: 10.18653/v1/2020.coling-main.398.

[22] M. Fu, C. Tantithamthavorn, T. Le, V. Nguyen, and D. Phung, "VulRepair: a T5-based automated software vulnerability repair," in *Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, Singapore Singapore: ACM, Nov. 2022, pp. 935–947. doi: 10.1145/3540250.3549098.

[23] C. S. Xia and L. Zhang, "Less training, more repairing please: revisiting automated program repair via zero-shot learning," in *Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, Singapore Singapore: ACM, Nov. 2022, pp. 959–971. doi: 10.1145/3540250.3549101.

[24] P. He, C. Meister, and Z. Su, "Structure-invariant testing for machine translation," in *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering*, Seoul South Korea: ACM, Jun. 2020, pp. 961–973. doi: 10.1145/3377811.3380339.

[25] S. Li *et al.*, "Hidden Backdoors in Human-Centric Language Models," in *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, Virtual Event Republic of Korea: ACM, Nov. 2021, pp. 3123–3140. doi: 10.1145/3460120.3484576.

[26] C. Watson, M. Tufano, K. Moran, G. Bavota, and D. Poshyvanyk, "On learning meaningful assert statements for unit test cases," in *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering*, Seoul South Korea: ACM, Jun. 2020, pp. 1398–1409. doi: 10.1145/3377811.3380429.

[27] T. Meinnel, C. Dian, and C. Giglione, "Myristoylation, an Ancient Protein Modification Mirroring Eukaryogenesis and Evolution," *Trends Biochem. Sci.*, vol. 45, no. 7, pp. 619–632, Jul. 2020, doi: 10.1016/j.tibs.2020.03.007.

[28] K. Dedes, A. B. Putra Utama, A. P. Wibawa, A. N. Afandi, A. N. Handayani, and L. Hernandez, "Neural Machine Translation of Spanish-English Food Recipes Using LSTM," *JOIV Int. J. Inform. Vis.*, vol. 6, no. 2, p. 290, Jun. 2022, doi: 10.30630/joiv.6.2.804.

[29] Y. Hu, W. Tao, Y. Xie, Y. Sun, and Z. Pan, "Token-level disentanglement for unsupervised text style transfer," *Neurocomputing*, vol. 560, p. 126823, Dec. 2023, doi: 10.1016/j.neucom.2023.126823.

[30] M. Işik and H. Dağ, "The impact of text preprocessing on the prediction of review ratings," *Turk. J. Electr. Eng. Comput. Sci.*, vol. 28, no. 3, pp. 1405–1421, May 2020, doi: 10.3906/elk-1907-46.

[31] M. Singh, R. Kumar, and I. Chana, "Corpus based Machine Translation System with Deep Neural Network for Sanskrit to Hindi Translation," *Procedia Comput. Sci.*, vol. 167, pp. 2534–2544, 2020, doi: 10.1016/j.procs.2020.03.306.

[32] G. Van Houdt, C. Mosquera, and G. Nápoles, "A review on the long short-term memory model," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 5929–5955, Dec. 2020, doi: 10.1007/s10462-020-09838-1.

[33] S. A. Mohamed, A. A. Elsayed, Y. F. Hassan, and M. A. Abdou, "Neural machine translation: past, present, and future," *Neural Comput. Appl.*, vol. 33, no. 23, pp. 15919–15931, Dec. 2021, doi: 10.1007/s00521-021-06268-0.

[34] L. Benkova, D. Munkova, Ľ. Benko, and M. Munk, "Evaluation of English–Slovak Neural and Statistical Machine Translation," *Appl. Sci.*, vol. 11, no. 7, p. 2948, Mar. 2021, doi: 10.3390/app11072948.

[35] C. Su, H. Huang, S. Shi, P. Jian, and X. Shi, "Neural machine translation with Gumbel Tree-LSTM based encoder," *J. Vis. Commun. Image Represent.*, vol. 71, p. 102811, Aug. 2020, doi: 10.1016/j.jvcir.2020.102811.

[36] W.-J. Ko *et al.*, "Adapting High-resource NMT Models to Translate Low-resource Related Languages without Parallel Data," in *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, Online: Association for Computational Linguistics, 2021, pp. 802–812. doi: 10.18653/v1/2021.acl-long.66.

[37] S. Mostafi, T. Alghamdi, and K. Elgazzar, "Interconnected Traffic Forecasting Using Time Distributed Encoder-Decoder Multivariate Multi-Step LSTM," in *2024 IEEE Intelligent Vehicles Symposium (IV)*, Jeju Island, Korea, Republic of: IEEE, Jun. 2024, pp. 2503–2508. doi: 10.1109/IV55156.2024.10588573.

[38] Y. Fan, F. Tian, Y. Xia, T. Qin, X.-Y. Li, and T.-Y. Liu, "Searching Better Architectures for Neural Machine Translation," *IEEEACM Trans. Audio Speech Lang. Process.*, vol. 28, pp. 1574–1585, 2020, doi: 10.1109/TASLP.2020.2995270.

[39] S. Edunov, M. Ott, M. Ranzato, and M. Auli, "On The Evaluation of Machine Translation Systems Trained With Back-Translation," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Online: Association for Computational Linguistics, 2020, pp. 2836–2846. doi: 10.18653/v1/2020.acl-main.253.

[40] N. Mathur, T. Baldwin, and T. Cohn, "Tangled up in BLEU: Reevaluating the Evaluation of Automatic Machine Translation Evaluation Metrics," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Online: Association for Computational Linguistics, 2020, pp. 4984–4997. doi: 10.18653/v1/2020.acl-main.448.

[41] B. Zhang, P. Williams, I. Titov, and R. Sennrich, "Improving Massively Multilingual Neural Machine Translation and Zero-Shot Translation," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Online: Association for Computational Linguistics, 2020, pp. 1628–1639. doi: 10.18653/v1/2020.acl-main.148.

[42] S.-P. Chuang, T.-W. Sung, A. H. Liu, and H. Lee, "Worse WER, but Better BLEU? Leveraging Word Embedding as Intermediate in Multitask End-to-End Speech Translation," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Online: Association for Computational Linguistics, 2020, pp. 5998–6003. doi: 10.18653/v1/2020.acl-main.533.

[43] D. Tay, "Turning metaphor on its head: a 'target-to-source transformation' approach in statistics education," *Front. Psychol.*, vol. 14, p. 1162925, Jun. 2023, doi: 10.3389/fpsyg.2023.1162925.

[44] A. Dalkıran *et al.*, "Transfer learning for drug–target interaction prediction," *Bioinformatics*, vol. 39, no. Supplement_1, pp. i103–i110, Jun. 2023, doi: 10.1093/bioinformatics/btad234.