Journal of Information Systems and Informatics
Vol. 5, No. 4, December 2023 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v5i4.597 Published By DRPM-UBD

Recurrent Neural Network-Gated Recurrent Unit for Indonesia-Sentani Papua Machine Translation

Rizkial Achmad [1], Yokelin Tokoro [2], Jusuf Haurissa [3], Andik Wijanarko[4]

[1,3] Information Systems Study Program, Faculty of Computer Science, Universitas Sains dan Teknologi, Jayapura, Papua, Indonesia.
[2] Information Systems Study Program, Faculty of Mathematics and Natural Sciences, Universitas Cenderawasih, Jayapura, Papua, Indonesia.
[4] Information Technology Study Program, Faculty of Computer Science, Universitas Amikom Purwokerto, Jawa Tengah Indonesia.
Email: [1]iky.mtech@gmail.com, [2]ytokoro87@gmail.com, [3]jhaurissa@gmail.com, [4]andikwijanarko@amikompurwokerto.ac.id

Abstract

The Papuan Sentani language is spoken in the city of Jayapura, Papua. The law states the need to preserve regional languages. One of them is by building an Indonesian-Sentani Papua translation machine. The problem is how to build a translation machine and what model to choose in doing so. The model chosen is Recurrent Neural Network – Gated Recurrent Units (RNN-GRU) which has been widely used to build regional languages in Indonesia. The method used is an experiment starting from creating a parallel corpus, followed by corpus training using the RNN-GRU model, and the final step is conducting an evaluation using Bilingual Evaluation Understudy (BLEU) to find out the score. The parallel corpus used contains 281 sentences, each sentence has an average length of 8 words. The training time required is 3 hours without using a GPU. The result of this research was that a fairly good BLEU score was obtained, namely 35.3, which means that the RNN-GRU model and parallel corpus produced sufficient translation quality and could still be improved.

.**Keywords**: Machine Translation, RNN-GRU, Sentani Papua, Indonesia.

1. INTRODUCTION

Indonesia has 718 regional languages based on 2019 data and Papua province has 326 regional languages [1]. As many as 80% of these regional languages have very vulnerable status, this is because the number of speakers is small because they are dominated by more dominant languages, which include the regional languages of Papua, West Papua, NTT and Maluku [2]. Papua has many ethnicities and sub-ethnicities with many different languages which are starting to enter the stage of language extinction [3]. One effort to preserve regional languages is to build national to regional language machine translations so that users understand regional language speakers [4]. Machine translation is software that is capable of changing one language into another different language [5]. Therefore, this research

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

aims to build an Indonesian-Sentani Papua language machine translation using the Recurrent Neural Network – Gated Recurrent Unit (RNN-GRU) model which can translate Indonesian into Sentani Papuan.

Previous research on machine translation from Indonesian to regional languages includes Indonesian to Lampung [6], Indonesian-Dayak language [7], Indonesian-Sambas language [8], Indonesian-Sundanese language [9], Ketapang[10] and Kawi[11]. Meanwhile, GRU is the state of the art of internal RNN which has been used to build an Indonesian-Sundanese language machine translation [4].

Machine translation is software that is able to translate source sentences into target sentences automatically [12]. Machine Translations are very helpful in translating source languages into target languages, for example from a foreign language to Indonesian or vice versa[13]. Various problems arise in translation activities, both carried out by humans and machine translators. Especially if the translation is context-based. These problems vary greatly due to geographic location, culture, habits and lexical differences [14]. Machine translation methods have experienced quite rapid development, starting from a rule-based method called Rule Base Machine Translation (RBMT) [15] [16] [17]. Based on statistics or what is called Statistical Machine Translation (SMT) [18], [19] [20], and which is the state of the art is an artificial neural network method called Neural Machine Translation (NMT) [21], [22][23].

The NMT approach cannot simply carry out language translation, an NMT contains a model structure, a process layer consisting of the methods used. NMT uses a modeling called Sequence To Sequence (SeqToSeq) [24] which can support the language translation process. In the SeqToSeq model there are two stages, namely Encoder and Decoder [25]. where the Encoder is a process layer that will enter the source language and the Decoder is a process layer that results from the translation of the Encoder layer which is converted into a target language or translated language [26]. The Encoder-Decoder layer consists of a learning process network using the Recurrent Neural Network (RNN) method [27].

2. METHODS

This research was carried out experimentally, starting from collecting data in the form of a parallel corpus of Indonesian-Papuan Sentani languages, then pre-processing the corpus and then training using the RNN-GRU model to produce a translation model. The translation model is used to translate Indonesian sentences into Sentani Papuan. The final step is to test the translation results using a model with translation results carried out by humans (human translators) using the BLEU measurement standard. The research procedure can be seen in the following picture.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

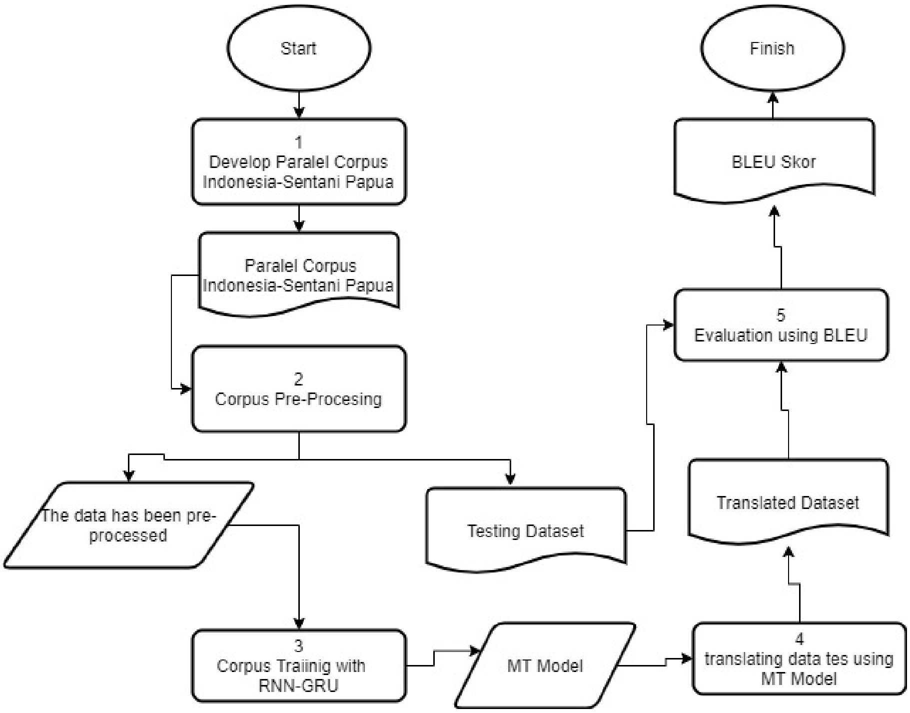

Figure 1. Research Procedure

The explanation of the image above is as follows.

2.1. Create Parallel Corpus

The Indonesian-Papuan Sentani language parallel corpus was created by translating Indonesian sentences into Papuan Sentani language. This translation activity was carried out by native Papuan Sentani language speakers. The parallel corpus contains 281 pairs of Indonesian-Sentani Papuan sentences.

2.2. Pre-processing

Before training is carried out on the dataset using the model, pre-processing is carried out on the parallel corpus with the aim of making the training process more optimal. The types of pre-processing carried out in this research include:

Lowercase, Lowercase changes all characters to non-capital letters, this aims to ensure that the same word is truly the same and is not differentiated by letters. For example, the words good and good are the same word. Lowercase is a pre-processing standard for machine translation which results in a smaller number of unique words, thereby reducing features.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Punctuation, this process removes punctuation marks in all sentences. The aim of removing punctuation marks is so that there are no additional words that contain punctuation marks so that the number of unique words that are features becomes smaller. This will result in the training process being faster and more accurate. Just like lowercase, punctuation is widely used as a pre-process in building machine translation.

2.3. Training Corpus using RNN-GRU

The main step of this research is the training dataset. The dataset in the form of a parallel corpus is trained using the RNN-GRU model. The RNN-GRU model has been used several times to build machine translations such as German-English machine translations [20], French, Arabic and Chinese to Urdu, Chinese-English with varying results.

RNN is a method that is often used in sequential data processing such as text processing and others [28]. An RNN represents a type of neural machine translation (NMT) system with three layers: an initial layer that assigns each word to a vector, like a word embedding or a one-hot word index; a looping hidden layer that continually computes and modifies the hidden state as it processes each word; and a final layer that predicts the likelihood of upcoming words while retaining the current hidden state [29]. The RNN scheme can be seen in the following image.

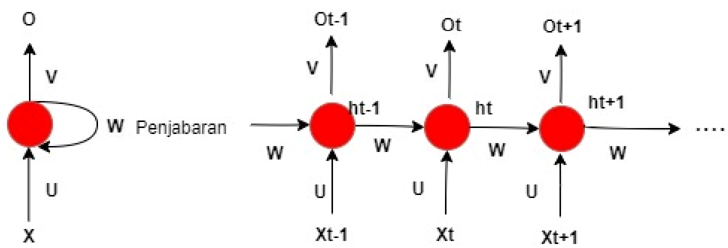

Figure 2. RNN Scheme [29].

GRU is a variant of Long Short Term Memory (LSTM) [30]. The GRU employs a pair of gates: the reset gate and the update gate. The reset gate is responsible for controlling the retention or removal of past information within the model. By considering both the previous state and upcoming input possibilities, it determines which information should be retained. On the other hand, the update gate aids the model in determining the extent to which previous information from the preceding time step should be preserved for the future. When an input enters the GRU model, it will first be processed by the update gate. An update gate functions as a mechanism that decides the quantity of past information to transmit to the future, employing an activation function [31]. The GRU scheme can be seen in the following image.

Journal of Information Systems and Informatics
Vol. 5, No. 4, December 2023

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

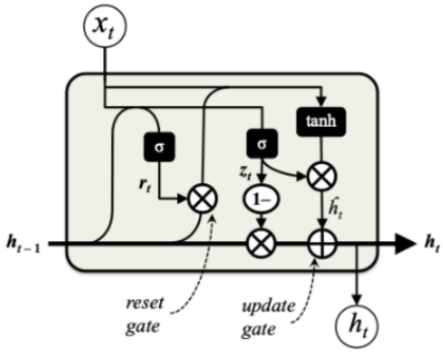

Figure 3. GRU Scheme [32]

Encoder-Decoder is a framework for the sequence to sequence method which consists of two parts. The first part is the Encoder which functions to vectorize words from the input sentence and the Decoder which functions to predict translated words from each vectorization value obtained from the Encoder [33]. The Encoder-Decoder scheme can be seen in the following image.

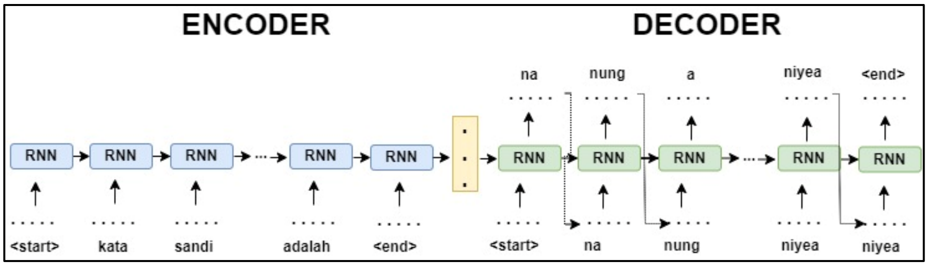

Figure 4. Encoder-Decoder Scheme

Each cell of the RNN model in the Encoder-Decoder schematic image in Figure 3 uses the GRU model. The model schematic can be seen in Figure 3. Meanwhile, the training parameter settings can be seen in Table 1.

Table 1. Training Parameters

No	Parameters	Value
1	Drop Out Layer	0.5
2	GRU Unit	1024
3	Activation Function	Softmax
4	Loss Function	Sparse categorical crossentropy
5	Validation Percentage	15
6	Epoch	10.000
7	Batch Size	64
8	Optimizer	RMSprop

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

2.4. Translating data test using MT model

The training dataset in the previous step will produce a machine translation model (MT Model). The next step is to translate the data for testing using the model. The result is Sentani Papuan sentences which are the result of translations from Indonesian using a machine translation model that has been created.

2.5. Evaluating Using BLEU

After the translation results using the previously created machine translation model have been successfully obtained, the next step is to measure the quality of the translation results by comparing them with the translation results made by humans (human translators). The method used is Bilingual Language Evaluation Understudy (BLEU), The BLEU formula is as shown in Equation 1 [34].

$$BLEU_{score} = BP * e^{\sum_{k=1}^{n} w_k \log(p_k)} \tag{1}$$

k is the number of n-grams being considered and w_k is how much weight the classification has on each n-gram. BP is the Brevity Penalty, which will have a value of 1 if the length of the hypothesis sentence (h) > The length of the reference sentence (r). if it is the same or vice versa, the BP formula is as show in Equation 2.

$$BP = e^{(1-\frac{r}{h})} \tag{2}$$

while p_k is the precision score for different n-grams. The p_k formula is as shown in Equation 3.

$$p_k = \frac{\sum_{C\varepsilon\,(candidates)} \sum_{n-gram\,\varepsilon\,C} Count_{clip}(n-gram)}{\sum_{C'\varepsilon\,(candidates)} \sum_{n-gram'\varepsilon\,C'} Count(n-gram')} \tag{3}$$

where C is the translated sentence while $Count_{clip}$ is the n-gram that matches the translated reference. The BLEU score for a usable machine translation is 30-60, more than 60, a score of more than 60 indicates that machine translation results exceed human translation.

3. RESULTS AND DISCUSSION

3.1. Dataset Description

The dataset used is in the form of a parallel corpus, namely a pair of Indonesian and Sentani Papuan languages where on average each Indonesian sentence contains 8 words. Each Indonesian sentence is paired with a Papuan Sentani sentence with a separating sign in the form of Tab. The following table shows the

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

first five lines and the last five lines of the Indonesian - Sentani Papua parallel corpus.

Table 2. Paralel Corpus

No	Indonesia	Sentani-Papua
1	Mari kita coba sesuatu	Meng nda rambung mokhomabhong
2	Aku harus pergi tidur	Reya jonggu re erelere
3	Saya harus tidur.	Reya jonggu re
4	Hari ini tanggal 18 Juni dan merupakan ulang tahunnya Muiriel!	Manaya 18 Juni, Muiriel re honggate ya
5	Hari ini tanggal 18 Juni dan Muiriel ulang tahun!	Manaya 18 Juni, Muiriel na ralo yakhama ya
…	…	…
277	Seharusnya kamu datang lebih awal.	Phu re anerhidere khena hele khale.
278	Apakah kamu sudah minum obat?	Rahe'phe ware mokhoroibhotere khena khoyea?
279	Sudah minum obat?	Raphi waneng're aneikondere khena khoyea?
280	Kau harus pergi tidur sekarang	Mai'nya ahusaei'se ra khena khale.
281	Sudahkah kamu menyerahkan laporanmu?	Perubahan phenate waneng jokho ereyea?

The parallel corpus contains 281 pairs of Indonesian Sentani Papuan sentences with an average length of Indonesian sentences of 8 words.

3.2. TrainingDatasets

The training of the parallel corpus was conducted on a robust hardware setup, featuring an Intel Core i5 11th Gen processor, complemented by 16 GB of RAM and a 500 GB SSD, ensuring efficient handling of the computational load. The software environment was Linux Ubuntu 22, providing a stable and reliable platform, with Python 3 as the chosen programming language for its versatility and widespread support in machine learning tasks. Notably, the dataset training was completed in a duration of 7 hours, a process conducted without the aid of a GPU (Graphic Processing Unit). This highlights the efficiency of the system despite the absence of specialized graphical processing hardware. The accuracy of the training at each epoch was meticulously recorded and is presented in the accompanying graph. This visual representation offers a clear view of the model's learning progression and accuracy improvements over time.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

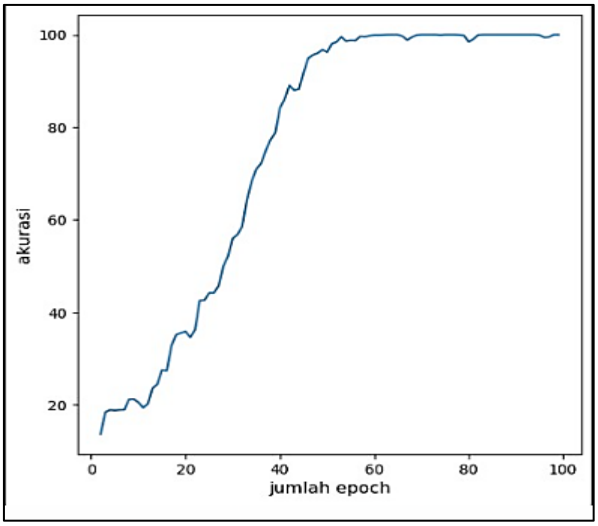

Figure 5. Accuracy graph on training dataset

The graph in Figure 6 shows that the level of accuracy on the training dataset is almost close to 100% when the number of epochs is between 40 and 60 epochs.

3.3. Evaluation

The final stage is to carry out an evaluation using BLEU. The results of this evaluation can be seen in the following image.

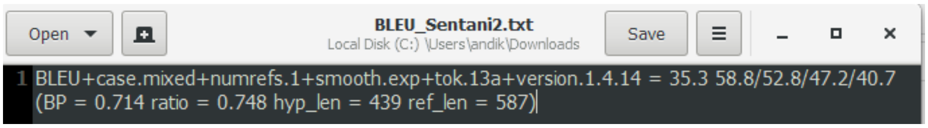

Figure 6. BLEU Score evaluation.

The image above can be explained using the following Table 3.

Table 3. BLEU score explanation

No	Evaluation	score
1	BLEU	35.3
2	Unigram	58.8
3	Bigram	52.8
4	Trigram	47.2
5	4-gram	40.7
6	Hypothesis length	439
7	Reference length	487

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

The data in Table 2 provides a comprehensive evaluation of a translation tool using various metrics. The BLEU score, standing at 35.3, is a significant indicator of translation quality. In the BLEU scoring system, which ranges from 0 to 100, a score of 35.3 suggests moderate effectiveness. This indicates that while the translation tool can produce generally accurate translations, there is still considerable room for improvement, especially in capturing finer nuances and contextual meanings.

The n-gram scores offer a more detailed insight into the translation tool's performance. The Unigram score of 58.8 suggests a high degree of accuracy in translating individual words. However, as we progress to more complex sequences, the accuracy decreases: the Bigram score is 52.8, indicating moderate success in translating two-word combinations; the Trigram score drops to 47.2, reflecting challenges in translating three-word phrases; and the 4-gram score further decreases to 40.7, highlighting difficulties in accurately translating sequences of four words.

Additionally, the comparison of hypothesis length (439 words) and reference length (487 words) in the translation points to a discrepancy in content capture. This difference suggests that while the tool is effective in translating most of the content, some parts of the original text might be either lost or inaccurately represented in the translation process.

In conclusion, while the translation tool shows a decent level of accuracy, particularly with individual words and short sequences, its effectiveness diminishes with longer and more complex word sequences. The BLEU score, alongside the n-gram analysis and the comparison of text lengths, collectively suggest that the tool is useful but requires enhancements to improve its accuracy in translating more complex text structures and to ensure a closer match to the original text's content and context.

4. CONCLUSION

The RNN-GRU (Recurrent Neural Network-Gated Recurrent Unit) model demonstrates potential in constructing a prototype machine translation system for Indonesian to Sentani Papuan languages. The evaluation of this model, based on the BLEU (Bilingual Evaluation Understudy) metric, yields a score of 35.3. This score indicates that while the translation quality is adequate, there is notable room for improvement. One viable approach to enhance the performance of this machine translation system could be to increase the quantity of the parallel corpus. Expanding the dataset with more diverse and extensive bilingual text examples could significantly refine the model's accuracy and effectiveness in handling the complexities of language translation between Indonesian and Sentani Papuan.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

5. ACKNOLEDGEMENT

This research was funded by the Ministry of Education, Culture, Research and Technology of the Republic of Indonesia through the Penelitian Dosen Pemula (PDP) Tahun Anggaran 2023.

REFERENCES

[1] Badan Pengembangan Bahasa dan Perbukuan Kemdikbud, "Peta Bahasa," Petabahasa.Kemdikbud.Go.Id. [Online]. Available: https://petabahasa.kemdikbud.go.id/

[2] S. Luturmas, T. Berlianty, and B. Agustina, "Pelestarian Bahasa Daerah Tanimbar Sebagai Upaya Perlindungan Ekspresi Budaya Tradisional," *TATOHI: Jurnal Ilmu Hukum*, vol. 2, no. 1, pp. 69–78, 2022, [Online]. Available: https://fhukum.unpatti.ac.id/jurnal/tatohi/article/view/897

[3] G. J. M. Mantiri and H. Ch. Iwong, "Eksistensi Bahasa Namblong dan Faktor-faktor Penyebab Pergeseran di Kabupaten Jayapura," *Hasta Wiyata*, vol. 6, no. 1, pp. 76–85, 2023, doi: 10.21776/ub.hastawiyata.2023.006.01.08.

[4] Y. Fauziyah, R. Ilyas, and F. Kasyidi, "Mesin Penterjemah Bahasa Indonesia-Bahasa Sunda Menggunakan Recurrent Neural Networks," *Jurnal Teknoinfo*, vol. 16, no. 2, p. 313, 2022, doi: 10.33365/jti.v16i2.1930.

[5] A. A. Suryani, I. Arieshanti, B. W. Yohanes, M. Subair, S. D. Budiwati, and B. S. Rintyarna, "Enriching English into Sundanese and Javanese translation list using pivot language," in *2016 International Conference on Information & Communication Technology and Systems (ICTS)*, 2016, pp. 167–171. doi: 10.1109/ICTS.2016.7910293.

[6] Z. Abidin, "Translation of Sentence Lampung-Indonesian Languages with Neural Machine Translation Attention Based Approach," *Inovasi Pembangunan : Jurnal Kelitbangan*, vol. 6, no. 02, pp. 191–206, 2018, doi: 10.35450/jip.v6i02.97.

[7] H. Sujaini, "Meningkatkan Peran Model Bahasa dalam Mesin Penerjemah Statistik (Studi Kasus Bahasa Indonesia-Dayak Kanayatn)," *Khazanah Informatika : Jurnal Ilmu Komputer dan Informatika*, vol. 3, no. 2, pp. 51–56, 2017, doi: 10.23917/khif.v3i2.4398.

[8] I. Hadi, "Uji Akurasi Mesin Penerjemah Statistik (MPS) Bahasa Indonesia Ke Bahasa Melayu Sambas Dan Mesin Penerjemah Statistik (MPS) Bahasa Melayu Sambas Ke Bahasa Indonesia," *Jurnal Sistem dan Teknologi Informasi*, vol. 2, pp. 1–6, 2014.

[9] Z. Abidin, "Penerapan Neural Machine Translation untuk Eksperimen Penerjemahan secara Otomatis pada Bahasa Lampung – Indonesia," *Prosiding Seminar Nasional Metode Kuantitatif 2017*, no. 978, pp. 53–68, 2017.

[10] W. Gunawan, H. Sujaini, and T. Tursina, "Analisis Perbandingan Nilai Akurasi Mekanisme Attention Bahdanau dan Luong pada Neural Machine

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Translation Bahasa Indonesia ke Bahasa Melayu Ketapang dengan Arsitektur Recurrent Neural Network," *Jurnal Edukasi dan Penelitian Informatika (JEPIN)*, vol. 7, no. 3, p. 488, 2021, doi: 10.26418/jp.v7i3.50287.

[11] I. G. B. A. Budaya, M. W. A. Kesiman, and I. M. G. Sunarya, "Perancangan Mesin Translasi berbasis Neural dari Bahasa Kawi ke dalam Bahasa Indonesia menggunakan Microframework Flask," *Jurnal Sistem dan Informatika (JSI)*, vol. 16, no. 2, pp. 94–103, 2022.

[12] H. Sujaini, "Peningkatan Akurasi Penerjemah Bahasa Daerah dengan Optimasi Korpus Paralel," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi (JNTETI)*, vol. 7, no. 1, 2018, doi: 10.22146/jnteti.v7i1.394.

[13] A. Faqih, "Penggunaan Google Translate Dalam Penerjemahan Teks Bahasa Arab Ke Dalam Bahasa Indonesia," *ALSUNIYAT: Jurnal Penelitian Bahasa, Sastra, dan Budaya Arab*, vol. 1, no. 2, pp. 88–97, 2018, doi: 10.17509/alsuniyat.v1i2.24216.

[14] J. Sheny *et al.*, "The source-target domain mismatch problem in machine translation," *ArXiv*, 2019.

[15] A. Alqudsi, N. Omar, and K. Shaker, "A Hybrid Rules and Statistical Method for Arabic to English Machine Translation," in *2nd International Conference on Computer Applications and Information Security, ICCAIS 2019*, IEEE, 2019. doi: 10.1109/CAIS.2019.8769545.

[16] M. Singh, R. Kumar, and I. Chana, "Improving Neural Machine Translation Using Rule-Based Machine Translation," *2019 7th International Conference on Smart Computing and Communications, ICSCC 2019*, pp. 1–5, 2019, doi: 10.1109/ICSCC.2019.8843685.

[17] J. Zhang, M. Utiyama, E. Sumita, G. Neubig, and S. Nakamura, "Improving neural machine translation through phrase-based soft forced decoding," *Machine Translation*, vol. 34, no. 1, pp. 21–39, 2020, doi: 10.1007/s10590-020-09244-y.

[18] L. Li, C. Parra Escartín, A. Way, and Q. Liu, "Combining translation memories and statistical machine translation using sparse features," *Machine Translation*, vol. 30, no. 3–4, pp. 183–202, 2016, doi: 10.1007/s10590-016-9187-6.

[19] P. Koehn, *Statistical Machine Translation*, no. 2. 2017. doi: 10.5565/rev/tradumatica.203.

[20] H. Cuong and K. Sima'an, *A survey of domain adaptation for statistical machine translation*, vol. 31, no. 4. Springer Netherlands, 2017. doi: 10.1007/s10590-018-9216-8.

[21] M. A. Haji Sismat, "Neural and Statistical Machine Translation: A comparative error analysis," in *Conference: 17th International Conference on Translation*, 2019.

[22] Y. Zhang and G. Liu, "Paragraph-Parallel based Neural Machine Translation Model with Hierarchical Attention," *J Phys Conf Ser*, vol. 1453, no. 1, 2020, doi: 10.1088/1742-6596/1453/1/012006.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[23] J. E. Ortega, R. Castro Mamani, and K. Cho, "Neural machine translation with a polysynthetic low resource language," *Machine Translation*, vol. 34, no. 4, pp. 325–346, 2021, doi: 10.1007/s10590-020-09255-9.

[24] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," *Adv Neural Inf Process Syst*, vol. 4, no. January, pp. 3104–3112, 2014.

[25] B. Van Merri and C. S. Fellow, "Learning Phrase Representations using RNN Encoder – Decoder for Statistical Machine Translation," in *Proceedings ofthe 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014, pp. 1724–1734.

[26] S. Garg, S. Peitz, U. Nallasamy, and M. Paulik, "Jointly learning to align and translate with transformer models," *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing, Proceedings of the Conference*, pp. 4453–4462, 2019, doi: 10.18653/v1/d19-1453.

[27] D. Britz, A. Goldie, M. T. Luong, and Q. V. Le, "Massive exploration of neural machine translation architectures," *EMNLP 2017 - Conference on Empirical Methods in Natural Language Processing, Proceedings*, pp. 1442–1451, 2017, doi: 10.18653/v1/d17-1151.

[28] Y. Liu, D. Zhang, L. Du, Z. Gu, J. Qiu, and Q. Tan, "A Simple but Effective Way to Improve the Performance of RNN-Based Encoder in Neural Machine Translation Task," in *2019 IEEE Fourth International Conference on Data Science in Cyberspace (DSC)*, 2019, pp. 416–421. doi: 10.1109/DSC.2019.00069.

[29] X. Wang, C. Chen, and Z. Xing, "Domain-specific machine translation with recurrent neural network for software localization," *Empir Softw Eng*, vol. 24, no. 6, pp. 3514–3545, 2019, doi: 10.1007/s10664-019-09702-z.

[30] A. Khan and A. Sarfaraz, "RNN-LSTM-GRU based language transformation," *Soft comput*, vol. 23, no. 24, pp. 13007–13024, 2019, doi: 10.1007/s00500-019-04281-z.

[31] A. Nilsen, "Perbandingan Model RNN, Model LSTM, dan Model GRU dalam Memprediksi Harga Saham-Saham LQ45," *Jurnal Statistika dan Aplikasinya*, vol. 6, no. 1, pp. 137–147, 2022, doi: 10.21009/jsa.06113.

[32] A. Lawi, H. Mesra, and S. Amir, "Implementation of Long Short-Term Memory and Gated Recurrent Units on Grouped Time-Series Data to Predict Stock Prices Accurately _ Research Square.pdf," *Res Sq*, 2021.

[33] L. Corallo, G. Li, K. Reagan, A. Saxena, A. S. Varde, and B. Wilde, "A Framework for German-English Machine Translation with GRU RNN," in *CEUR Workshop Proceedings*, 2022.

[34] S. Chauhan and P. Daniel, "A Comprehensive Survey on Various Fully Automatic Machine Translation Evaluation Metrics," *Neural Process Lett*, 2022, doi: 10.1007/s11063-022-10835-4.