# WMT24 System Description for the MultiIndic22MT Shared Task on Manipuri Language

**Ningthoujam Justwant Singh**, **Kshetrimayum Boynao Singh**,

**Ningthoujam Avichandra Singh**, **Sanjita Phijam**, and **Thoudam Doren Singh**

Centre for Natural Language Processing (CNLP) & Dept. of CSE, NIT Silchar, India

{njustwant92,boynfrancis,avichandra0420,phijamsan.jk,thoudam.doren}@gmail.com

## Abstract

This paper presents a Transformer-based Neural Machine Translation (NMT) system developed by the Centre for Natural Language Processing and the Department of Computer Science and Engineering at the National Institute of Technology Silchar, India (NITS-CNLP) for the MultiIndic22MT 2024 Shared Task. The system focused on the English-Manipuri language pair for the WMT24 shared task. The proposed WMT system shows a BLEU score of 6.4, a chrF score of 28.6, and a chrF++ score of 26.6 on the public test set Indic-Conv dataset. Further, in the public test set Indic-Gen dataset, it achieved a BLEU score of 8.1, a chrF score of 32.1, and a chrF++ score of 29.4 on the English-to-Manipuri translation.

## 1 Introduction

The Centre for Natural Language Processing and the Department of Computer Science and Engineering at the National Institute of Technology Silchar, India (NITS-CNLP) participated in The MultiIndic22MT 2024 Shared Task (Dabre and Kunchukuttan, 2024) for English-Manipuri language pair in the WMT2024 shared task. The shared task involves developing Machine Translation (MT) for English and 22 Indic Languages (Assamese, Bengali, Bodo, Dogri, Konkani, Gujarati, Hindi, Kannada, Kashmiri (Arabic script), Maithili, Malayalam, Marathi, Manipuri (Meitei script), Nepali, Oriya, Punjabi, Sanskrit, Santali, Sindhi (Devanagari script), Tamil, Telugu, Urdu).

In recent years, there has been growing interest in developing effective machine translation systems for Manipuri (Singh et al., 2023a) (Singh and Singh, 2020) (Singh and Singh, 2022b) (Singh et al., 2023b), which is a language with a complex linguistic structure (Singh and Bandyopadhyay, 2010) and limited bitext. Various approaches have been explored to create models that can accurately translate between Manipuri and other languages(Singh and Singh, 2022a). These efforts include the development of translation models that handle different scripts, such as Bengali and Meitei Mayek, and the integration of linguistic (Singh and Bandyopadhyay, 2005) (Singh and Bandyopadhyay, 2010) and that are essential for producing high-quality translations.

### 1.1 Brief Description of Manipuri language

The Manipuri language can be written in: Bengali and Meitei Mayek. It is one of the 22 official languages of India included in the 8$^{th}$ schedule of the Indian constitution. Historically, computational linguistics research and translation efforts for Manipuri have predominantly focused on the Bengali script, due to its extensive availability of digital resources.

Most English-to-Manipuri translation models and linguistic resources have been developed using the Bengali script. Numerous projects have created bitext and bilingual dictionaries in this script, significantly advancing machine translation for Manipuri.

In contrast, the Meitei Mayek script, which holds cultural and historical significance for the Manipuri people, has not received similar attention. Although recent years have seen a revival of the Meitei Mayek script, highlighting the need for computational resources and tools to support its use in modern digital contexts, it still faces challenges due to the limited availability of textual data and digital resources.

Efforts to address this gap include digitizing ancient manuscripts and developing new textual resources in Meitei Mayek.

## 2 Our Approaches

### 2.1 Dataset and Preprocessing

The training dataset (Gala et al., 2023) provided by the WMT Shared Task 2024 consists of 42,740 bitext. After incorporating additional data from the



*Proceedings of the Ninth Conference on Machine Translation (WMT)*, pages 797–803
November 15–16, 2024. ©2024 Association for Computational Linguistics

| Language | Sentence | Word |
|---|---|---|
| **English-Training** | 63506 | 1093014 |
| **Manipuri-Training** | 63506 | 894411 |
| **English-Validation** | 997 | 30772 |
| **Manipuri-Validation** | 997 | 31799 |
| **English-Testing$_{\mathbf{conv}}$** | 1502 | 14849 |
| **Manipuri-Testing $_{\mathbf{conv}}$** | 1502 | 12621 |
| **English-Testing $_{\mathbf{gen}}$** | 1023 | 25347 |
| **Manipuri-Testing $_{\mathbf{gen}}$** | 1023 | 23421 |

Table 1: This table presents the BLEU, chrF, and chrF++ scores for the English-to-Manipuri machine translation system.

Ministry of Electronics and Information Technology (MeitY), we ensure that the dataset is properly aligned to each other to confirm that it consists of bitext, along with removing duplicates and noise. As a result, we obtain a clean training dataset of 63,506 bitext. The validation dataset, also provided by the WMT Shared Task 2024, contains 997 bitext. For testing, we use the test set from the WMT Shared Task 2024, which includes the Indic-Conv and Indic-Gen datasets, comprising 1,502 and 1,023 bitext, respectively.

## 2.2 Hyperparameter

### 2.2.1 Sentencepiece Model

We train a model ($MT_{sp}$) system based on a basic Transformer architecture (Vaswani et al., 2017), utilizing the OpenNMT toolkit (Klein et al., 2017)[1]. In this model, we employ the SentencePiece (Kudo, 2018)[2] tokenization technique with a vocabulary size of 8,000 for both English and Manipuri. The model consists of 6 encoder and 6 decoder layers, each with 8 attention heads. The $MT_{sp}$ system is trained for 200,000 steps, with validation conducted every 5,000 steps, and model checkpoints saved at 5,000-step intervals.

It utilizes a bucket size of 262,144 and a batch size of 2048, along with 8,000 warmup steps. Optimization is performed using the Adam optimizer (Kingma and Ba, 2014). The ($MT_{sp}$) is trained with a feed-forward layer size of 2048, a hidden size of 512, and a label smoothing of 0.1.

### 2.2.2 Proposed Subword Model

Our proposed model ($WMT24_{proposed}$) is also a transformer model trained using the OpenNMT toolkit. For tokenization, we employ the Byte Pair Encoding (BPE) method (Sennrich et al., 2016)[3] with the same vocab size 8000 for English and Manipuri. The proposed model shares the same hyperparameters as the ($MT_{sp}$), including training for 200,000 steps, with validation every 5,000 steps, and model checkpoints saved at 5,000-step intervals. It also uses the same bucket size of 262,144 and a batch size of 2048.

Both the ($MT_{sp}$) and ($WMT24_{proposed}$) models are configured with 8 attention heads, 6 encoder layers, 6 decoder layers, and a learning rate of 2, along with an attention dropout rate of 0.1. Optimization is performed using the Adam optimizer (Kingma and Ba, 2014), and the models share identical hyperparameters, including a feed-forward layer size of 2048, a hidden size of 512, and label smoothing of 0.1.

We train both the $WMT24_{proposed}$ and $MT_{sp}$ models using the complete set of 63,506 sentence pairs, which includes data from both the WMT Shared Task data and additional data provided by MeitY. We utilize the same validation sentences, and the testing data remains unchanged.

The performance of each model is evaluated using BLEU (Papineni et al., 2002), chrF (Popović, 2015), and chrF++ (Popović, 2017) metrics, utilizing the sacreBLEU tool (Post, 2018)[4] for score evaluation.

# 3 Results and Discussion

In this section, we discuss the experimental results and performance of the models. The reported BLEU, chrF, and chrF++ scores are calculated based on the de-tokenized text. The scores of the systems are given in Table 2. The English-to-Manipuri translation $WMT24_{proposed}$ model achieves a BLEU score of **6.4**, a chrF score of 28.6, and a chrF++ score of 26.6 on the Indic-Conv dataset. In contrast, the $MT_{sp}$ achieves a BLEU score of 5.1, a chrF score of 30.9, and a chrF++ score of 27.1 on the same dataset.

For the Indic-Gen dataset, the $WMT24_{proposed}$ achieves a BLEU score of **8.1**, a chrF score of 32.1, and a chrF++ score of 29.4, while the $MT_{sp}$ achieves a BLEU score of 6.8, a chrF score of 32.8, and a chrF++ score of 28.7. These results highlight the superior performance of the $WMT24_{proposed}$ compared to the $MT_{sp}$ model across all evaluation metrics.

[1]https://github.com/OpenNMT/OpenNMT
[2]https://github.com/google/sentencepiece
[3]https://github.com/rsennrich/subword-nmt
[4]https://github.com/mjpost/sacrebleu

| MT systems | Test Set | BLEU | chrF | chrF++ |
|---|---|---|---|---|
| WMT24 $_{\text{proposed}}$ | conv | **6.4** | **28.6** | **26.6** |
| $\text{MT}_{\text{sp}}$ | conv | 5.1 | 30.9 | 27.1 |
| WMT24 $_{\text{proposed}}$ | gen | **8.1** | **32.1** | **29.4** |
| $\text{MT}_{\text{sp}}$ | gen | 6.8 | 32.8 | 28.7 |

Table 2: This table presents the BLEU, chrF, and chrF++ scores for the English-to-Manipuri machine translation system.

### 3.1 Qualitative Analysis

In the table 3, sample 1, the word ꯍꯌꯦꯡ, meaning "tomorrow" is correctly translated in both models. The word "movie" has been translated to a more beautiful word in both translations as ꯃꯃꯤ ꯀꯨꯝꯍ, which we call movies in the early period, while in the reference, it is translated as cinema, which is not so accurate. While "Mom" has been translated as ꯍꯣꯝ in the reference but it is transliterated in $\text{MT}_{\text{sp}}$ ꯃꯣꯝ. In the second sample, the phrase "school and I" is accurately translated; the reference ꯑꯩ ꯁꯀꯨꯜ is correctly represented in the output as ꯑꯩꯅ ꯁꯀꯨꯜ, but the overall meaning of the sentence is not conveyed as the reference text is "not to go" while both translations have translated it as "go". In the third sample, the word "holiday" is translated properly, with the reference being ꯁꯨꯃꯤꯗꯦ꯫, here both models show a better translation than the reference text. In the fourth sample, the phrase "14 April right" is accurately translated as ꯑꯦꯞꯔꯤꯜ ꯱꯴, but in the $\text{WMT24}_{\text{proposed}}$, the word o.t.p ꯑꯣ.ꯇꯤ.ꯄꯤ has been included, which changes the overall meaning. In the fifth sample, the name "Lelina" is correctly translated as ꯂꯦꯂꯤꯅꯥ in the $\text{WMT24}_{\text{proposed}}$, but the meaning of the sentence cannot be conveyed as the phrase "thank you" has not been translated. The word "thank you" has been translated in the $\text{MT}_{\text{sp}}$. Still, the name "Lelina" is not translated. In the sixth sample, "Ambedkar Jayanti" is correctly translated as ꯑꯝꯕꯦꯗꯀꯔ ꯖꯌꯟꯇꯤ in the $\text{WMT24}_{\text{proposed}}$ model; however, the adequacy is hampered by the missing translation of "tomorrow" in the output, and the fluency is also affected by the ill-formed sentence structure. Meanwhile, in the $\text{MT}_{\text{sp}}$ model, the word "Jayanti" is missing. In sample 7, the word "municipal" ꯃ꯭ꯌꯨꯅꯤꯁꯤꯄꯥꯜ has been translated in both models, while $\text{MT}_{\text{sp}}$ performs better. Some keywords have been translated like the "senior citizen" ꯁꯤꯅꯤꯌꯔ ꯁꯤꯇꯤꯖꯦꯟꯁꯤꯡ. In sample 8, the word "motorcycle" ꯃꯣꯇꯔꯁꯥꯏꯀꯜ is included in the $\text{WMT24}_{\text{proposed}}$, which is an extra word.

In the table 4, sample 1, the words "shoes," "clothes," "tie," "jewelry," "hairstyle," "make-up," "watch," "cosmetics," and "perfume" have been translated in both models. In the second sample, "dry" is translated as ꯑꯀꯪꯕ and "stone" as ꯅꯨꯡꯅ; in both samples, the overall meaning is conveyed. In sample 3, "chilli powder" ꯃꯔꯤꯆꯤ ꯃꯀꯨꯞ has been translated correctly. In sample 4, the phrase "metro station" has been translated correctly in both models, but in this case, the $\text{MT}_{\text{sp}}$ model performs better. In the sample 5, the word "Xeres" has not been translated, and the overall meaning of the sentence cannot be conveyed. In the last sample, while the output contains some keywords from the reference, it fails to translate the overall meaning of the sentence.

Four native speakers assessed the adequacy and fluency of the translations. The overall output of the sample has been shown in the figure 1. This evaluation indicates the quality of the sample outputs, reflecting how fluent and adequate the translations are in conveying the intended meaning.

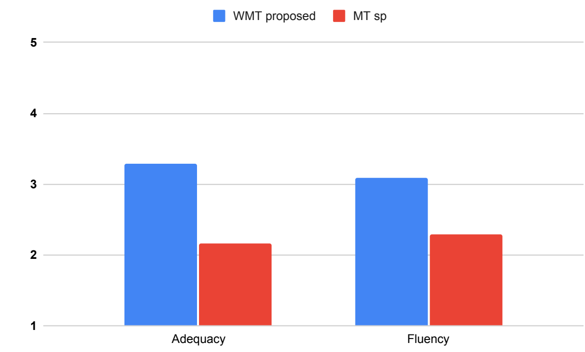


Figure 1: Adequacy and Fluency for the output samples

## 4 Conclusion

We develop and evaluate two Transformer-based machine translation (MT) systems tested on two different datasets (Indic-Conv and Indic-Gen) for translating English to Manipuri. One system ($\text{MT}_{\text{sp}}$) utilizes the OpenNMT toolkit with Senten-

| Result | Samples for Indic22-Conv test dataset |
|---|---|
| **Source 1:** | Mom, let's go for a movie tomorrow. |
| **Reference 1:** | ꯏꯃꯥ, ꯍꯌꯦꯡ ꯁꯤꯅꯦꯃꯥ ꯑꯃ ꯌꯦꯡꯕ ꯆꯠꯅꯨꯁꯦ꯫ |
| **WMT24$_{proposed}$ 1:** | ꯍꯣꯝ ꯑꯁꯤ ꯍꯌꯦꯡꯒꯤ ꯃꯃꯤ ꯀꯨꯝꯍꯩ ꯑꯃꯒꯤꯗꯃꯛ ꯆꯠꯀꯁ ꯑꯣꯏ ꯫ |
| **MT$_{sp}$ 1:** | ꯃꯣꯝ, ꯍꯌꯦꯡ ꯃꯃꯤ ꯀꯨꯝꯍꯩ ꯑꯃ ꯆꯠꯅꯤ꯫ |
| **Source 2:** | I don't have to go to school. |
| **Reference 2:** | ꯑꯩ ꯁ꯭ꯀꯨꯜ ꯆꯠꯅꯣꯏ ꯫ |
| **WMT24$_{proposed}$ 2:** | ꯑꯩꯅ ꯁ꯭ꯀꯨꯜ ꯀꯥꯕ ꯇꯣꯔꯤ꯫ |
| **MT$_{sp}$ 2:** | ꯑꯩ ꯁ꯭ꯀꯨꯜ ꯆꯠꯅꯤ ꯫ |
| **Source 3:** | It is a holiday. |
| **Reference 3:** | ꯁꯨꯇꯤꯅꯦ꯫ |
| **WMT24$_{proposed}$ 3:** | ꯃꯁꯤ ꯁꯨꯇꯤ ꯑꯃꯅꯤ꯫ |
| **MT$_{sp}$ 3:** | ꯃꯁꯤ ꯁꯨꯇꯤ ꯅꯨꯃꯤꯠꯅꯤ꯫ |
| **Source 4:** | Oh, tomorrow is the 14th of April right? |
| **Reference 4:** | ꯑꯣ, ꯍꯌꯦꯡꯁꯦ ꯑꯦꯄ꯭ꯔꯤꯜꯒꯤ ꯱꯴ ꯆꯨꯝꯃꯣ ? |
| **WMT24$_{proposed}$ 4:** | ꯑꯣ.ꯌꯣꯤ.ꯌꯨꯤ. ꯑꯁꯤ ꯑꯦꯄ꯭ꯔꯤꯜ ꯱꯴ꯗꯅꯤ꯫ |
| **MT$_{sp}$ 4:** | ꯑꯣ, ꯍꯌꯦꯡꯒꯤ ꯑꯦꯄ꯭ꯔꯤꯜ ꯱꯴ ꯑꯁꯤꯅꯤ |
| **Source 5:** | Thank you, Lelina. |
| **Reference 5:** | ꯊꯥꯒꯠꯆꯔꯤ, ꯂꯦꯂꯤꯅꯥ꯫ |
| **WMT24$_{proposed}$ 5:** | ꯅꯍꯥꯛꯅ ꯊꯒꯅꯕꯗꯤ, ꯂꯦꯂꯤꯅꯥ ꯍꯥꯌꯕꯤꯕꯨ꯫ |
| **MT$_{sp}$ 5:** | ꯑꯗꯣꯝꯕꯨ ꯊꯥꯒꯠꯆꯔꯤ |
| **Source 6:** | It is Ambedkar Jayanti tomorrow! |
| **Reference 6:** | ꯍꯌꯦꯡ ꯑꯝꯕꯦꯗꯀꯔ ꯖꯌꯦꯟꯇꯤ ꯅꯦ! |
| **WMT24$_{proposed}$ 6:** | ꯃꯁꯤ ꯑꯝꯕꯦꯗꯀꯔ ꯖꯌꯟꯇꯤ! |
| **MT$_{sp}$ 6:** | ꯃꯁꯤ ꯍꯌꯦꯡꯗꯤ ꯑꯝꯕꯦꯗꯛꯔ |
| **Source 7:** | Even the municipal corporation people also worked round the clock so that they can get the electricity back on time as there were kids and senior citizens present who were facing a lot of difficulties. |
| **Reference 7:** | [illegible] |
| **WMT24$_{proposed}$ 7:** | [illegible] |
| **MT$_{sp}$ 7:** | [illegible] |
| **Source 8:** | There are a lot of organisations here which are catering help to the people, in terms of groceries, medical facilties and medicines and all the necessary items as and when it is needed. |
| **Reference 8:** | [illegible] |
| **WMT24$_{proposed}$ 8:** | [illegible] |
| **MT$_{sp}$ 8:** | [illegible] |

Table 3: Sample input and output of the English to Manipuri MT system on the Indic22-Conv test dataset.

| Result | Samples for Indic22-Gen test dataset |
|---|---|
| **Source 1:** | An appearance is a bunch of attributes related to the service person, like their shoes, clothes, tie, jewellery, hairstyle, make-up, watch, cosmetics, perfume, etc |
| **Reference 1:** | [illegible] |
| **WMT24$_{proposed}$ 1:** | [illegible] |
| **MT$_{sp}$ 1:** | [illegible] |
| **Source 2:** | Make this into powder with a dry grinder or in a stone pestle. |
| **Reference 2:** | [illegible] |
| **WMT24$_{proposed}$ 2:** | [illegible] |
| **MT$_{sp}$ 2:** | [illegible] |
| **Source 3:** | The use of chilli powder in this region is done cautiously. |
| **Reference 3:** | [illegible] |
| **WMT24$_{proposed}$ 3:** | [illegible] |
| **MT$_{sp}$Output 3:** | [illegible] |
| **Source 4:** | The nearest Delhi Metro station is Arjan Garh, on the Yellow Line. |
| **Reference 4:** | [illegible] |
| **WMT24$_{proposed}$ 4:** | [illegible] |
| **MT$_{sp}$ 4:** | [illegible] |
| **Source 5:** | After him, came Xerxes II for a short while. |
| **Reference 5:** | [illegible] *II* [illegible] |
| **WMT24$_{proposed}$ 5:** | [illegible] *XII* [illegible] |
| **MT$_{sp}$ 5:** | [illegible] *XI* [illegible] |
| **Source 6:** | In Karaikal liquor is cheaper than in the neighbouring Tamil Nadu, there are quite a few decent bars in Karaikal - the Niagra bar in the Nanda hotel, the Thunder bar in the Paris International, the City bar - a very famous one in the town, and The Sea Gulls Restaurant owned by the government of Pondicherry which is at the sea shore and is good to hang out in the evenings. |
| **Reference 6:** | [illegible] |
| **WMT24$_{proposed}$ 6:** | [illegible] |
| **MT$_{sp}$Output 6:** | [illegible] |

Table 4: Sample Input and Output of the English to Manipuri MT System on the Indic22-Gen test dataset.

cepiece tokenization for tokenization, while the proposed model (WMT24$_{proposed}$) employs the OpenNMT toolkit with Byte Pair Encoding (BPE). Both models are trained on a comprehensive dataset that includes data from WMT24 and MeitY.

The model is optimized with the Adam optimizer and is evaluated using BLEU, chrF, and chrF++ metrics. Additionally, the translations are assessed for both adequacy and fluency. The models successfully convey the overall meaning of the source sentences, but they often lack fluency, producing disjointed or grammatically incorrect outputs.

Overall, the $\text{WMT24}_{\text{proposed}}$ produces translations that are more syntactically correct, contextually appropriate, and idiomatically fluent, while $\text{MT}_{\text{sp}}$ offers more direct, simpler translations that sometimes lose nuance or complex structure.

## Limitations

The proposed ($\text{WMT24}_{\text{proposed}}$) model translation conveys the main ideas of the reference sentence, despite certain errors and structural challenges. It captures some aspects of the overall meaning of the reference sentences. In the case of longer sentences, there is a large amount of adequacy. However, the fluency of these translations deteriorates as the length of the input sentences increases.

## Acknowledgements

This study is funded by the Ministry of Electronics and Information Technology (MeitY), Government of India, under Ref. No. 11(1)/2022-HCC(TDIL)-Part(4). We would like to express our gratitude to the CNLP Lab and the Department of Computer Science and Engineering at NIT Silchar for their essential role in providing the computing resources used in this research.

## References

Raj Dabre and Anoop Kunchukuttan. 2024. Findings of wmt 2024's multiindic22mt shared task for machine translation of 22 indian languages. In *Proceedings of the Ninth Conference on Machine Translation*, Miami. Association for Computational Linguistics.

Jay Gala, Pranjal A Chitale, A K Raghavan, Varun Gumma, Sumanth Doddapaneni, Aswanth Kumar M, Janki Atul Nawale, Anupama Sujatha, Ratish Puduppully, Vivek Raghavan, Pratyush Kumar, Mitesh M Khapra, Raj Dabre, and Anoop Kunchukuttan. 2023. Indictrans2: Towards high-quality and accessible machine translation models for all 22 scheduled indian languages. *Transactions on Machine Learning Research*.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. OpenNMT: Open-source toolkit for neural machine translation. In *Proceedings of ACL 2017, System Demonstrations*, pages 67–72, Vancouver, Canada. Association for Computational Linguistics.

T Kudo. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. *arXiv preprint arXiv:1808.06226*.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on association for computational linguistics*, pages 311–318. Association for Computational Linguistics.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.

Maja Popović. 2017. chrF++: words helping character n-grams. In *Proceedings of the Second Conference on Machine Translation*, pages 612–618, Copenhagen, Denmark. Association for Computational Linguistics.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Kshetrimayum Boynao Singh, Avichandra Singh Ningthoujam, Loitongbam Sanayai Meetei, Sivaji Bandyopadhyay, and Thoudam Doren Singh. 2023a. NITS-CNLP low-resource neural machine translation systems of English-Manipuri language pair. In *Proceedings of the Eighth Conference on Machine Translation*, pages 967–971, Singapore. Association for Computational Linguistics.

Kshetrimayum Boynao Singh, Ningthoujam Avichandra Singh, Loitongbam Sanayai Meetei, Ningthoujam Justwant Singh, Thoudam Doren Singh, and Sivaji Bandyopadhyay. 2023b. A comparative study of transformer and transfer learning MT models for English-Manipuri. In *Proceedings of the 20th International Conference on Natural Language Processing (ICON)*, pages 791–796, Goa University, Goa, India. NLP Association of India (NLPAI).

Salam Michael Singh and Thoudam Doren Singh. 2020. Unsupervised neural machine translation for English and Manipuri. In *Proceedings of the 3rd Workshop on Technologies for MT of Low Resource Languages*, pages 69–78, Suzhou, China. Association for Computational Linguistics.

Salam Michael Singh and Thoudam Doren Singh. 2022a. An empirical study of low-resource neural machine translation of manipuri in multilingual settings. *Neural Comput. Appl.*, 34(17):14823–14844.

Salam Michael Singh and Thoudam Doren Singh. 2022b. Low resource machine translation of english–manipuri: A semi-supervised approach. *Expert Systems with Applications*, 209:118187.

Thoudam Doren Singh and Sivaji Bandyopadhyay. 2005. Manipuri morphological analyzer. In *In the Proceedings of the Platinum Jubilee International Conference of LSI, Hyderabad, India*.

Thoudam Doren Singh and Sivaji Bandyopadhyay. 2010. Manipuri-English bidirectional statistical machine translation systems using morphology and dependency relations. In *Proceedings of the 4th Workshop on Syntax and Structure in Statistical Translation*, pages 83–91, Beijing, China. Coling 2010 Organizing Committee.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.