

WMT24 System Description for the MultiIndic22MT Shared Task on Manipuri Language

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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 8th 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

Language	Sentence	Word
English-Training	63506	1093014
Manipuri-Training	63506	894411
English-Validation	997	30772
Manipuri-Validation	997	31799
English-Testing_{conv}	1502	14849
Manipuri-Testing_{conv}	1502	12621
English-Testing_{gen}	1023	25347
Manipuri-Testing_{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 _{proposed}	conv	6.4	28.6	26.6
MT _{sp}	conv	5.1	30.9	27.1
WMT24 _{proposed}	gen	8.1	32.1	29.4
MT _{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 𑜁𑜃𑜂𑜆, meaning “tomorrow” is correctly translated in both models. The word “movie” has been translated to a more beautiful word in both translations as 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆, 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 𑜁𑜃𑜂𑜆 in the reference but it is transliterated in MT_{sp} 𑜁𑜃𑜂𑜆. In the second sample, the phrase “school and I” is accurately translated; the reference 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆 is correctly represented in the output as 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆, 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 𑜁𑜃𑜂𑜆, here both models show a better translation than the reference text. In the fourth sample, the phrase “14 April right” is accurately translated as 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆, but in the WMT24_{proposed}, the word o.t.p 𑜁𑜃𑜂𑜆 has been included, which changes the overall meaning. In the fifth sample, the name “Lelina” is correctly translated as 𑜁𑜃𑜂𑜆 in the WMT24_{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 MT_{sp}. Still, the name “Lelina” is not translated. In the sixth sample, “Ambedkar Jayanti” is correctly translated as 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆 in the WMT24_{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 MT_{sp} model, the word “Jayanti” is missing. In sample 7, the word “municipal” 𑜁𑜃𑜂𑜆 has been translated in both models, while MT_{sp} performs better. Some keywords have been translated like the “senior citizen” 𑜁𑜃𑜂𑜆 𑜁𑜃𑜂𑜆. In sample 8, the word “motorcycle” 𑜁𑜃𑜂𑜆 is included in the WMT24_{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 𑜁𑜃𑜂𑜆 and “stone” as 𑜁𑜃𑜂𑜆; in both samples, the overall meaning is conveyed. In sample 3, “chilli powder” 𑜁𑜃𑜂𑜆 has been translated correctly. In sample 4, the phrase “metro station” has been translated correctly in both models, but in this case, the MT_{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.

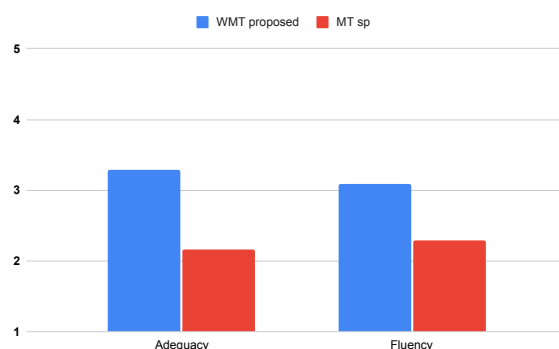


Figure 1: Adequacy and Fluency for the output samples

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 (MT_{sp}) utilizes the OpenNMT toolkit with Senten-

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 WMT24_{proposed} produces translations that are more syntactically correct, contextually appropriate, and idiomatically fluent, while MT_{sp} offers more direct, simpler translations that sometimes lose nuance or complex structure.

Limitations

The proposed (WMT24_{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.

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