The WER margin for Formal Words and Named Entity using `Syllable Tagging` model is considerably low in terms of percentage proven by how low the margin between each dataset WER with the average value of each WER. It can be happened because it use the same model from combined dataset for the training data. Table. III compares other Indonesian Syllabification models with this Transformer model with and without `Syllable Tagging`. Comparing with other deep learning model, this Transformer model is better than BiLSTM-CNN-CRF in terms of Named Entity WER with 1.02% margin but the WER for Formal Words still lower than this model with 0.88% margin. It happens because the BiLSTM-CNN-CRF using augmented 50k Formal Words that turn into 12.8M valid augmented words for training, thus the result is better when tested with Formal Words and because Named Entity Words have some unique syllable that could be not included in the vocabulary of the model and causing false prediction. This Transformer model have lower average WER percentage than the BiLSTM-CNN-CRF model with 3.68% compared to 3.75%.

TABLE III
MODEL COMPARATIONS

Model	WER_{FW}	WER_{NE}	$\overline{WER}$
Rule-based [11]	-	2.9%	2.9%
BiLSTM-CNN-CRF [8]	2.50%	5.01%	3.75%
Transformer$_{withoutST}$	18.2%	26.7%	22.4%
Transformer$_{withST}$	3.38%	3.99%	3.68%

ST : Syllable Tagging FW : Formal Words
NE : Named Entity

V. Conclusion

This Transformer model with `Syllable Tagging` has similar WER for both Formal Words and Named Entity which depicts this model can be used universally for Indonesian words. This model has a lower WER average than the other Indonesian syllabification deep learning model with 3.68% compared to 3.75% BiLSTM-CNN-CRF average WER which proves that this model performs better than the previous deep learning model with the same dataset.

Improved WER for syllabification can open up opportunities to have more accurate spelling of a word which opens up another opportunity to have better pronunciation for Indonesian language text-to-speech. Minor works can be done using different deep learning methods that still use `Syllable Tagging` method. Future works from this paper can be improving the model at the phonemic level to represent more accuracy for text-to-speech.

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