occurred as much as 2.03% compared to the baseline. The increase in accuracy of each model from the baseline to the best final result is shown in Table IX.

TABLE IX
BEST PERFORMANCE OF ALL MODELS

Model	Accuracy (%)
CNN	82.93 (+0.63)
BiLSTM	84.25 (+2.03)
CNN-BiLSTM	83.01 (+0.99)
BiLSTM-CNN	83.43 (+1.03)

IV. CONCLUSION

In this study, depression detection on the X social media platform is performed using an attention-based CNN-BiLSTM hybrid deep learning model, utilizing TF-IDF for feature extraction and FastText for feature expansion. This research uses text datasets from user tweets in Indonesian and translated English with a total of 50,523 data and constructs a similarity corpus with a total of 100,594 data. In testing, five scenarios were carried out to find the best accuracy. Among them are choosing the best split ratio, the best n-gram, the best number of max features, feature expansion with FastText, and the attention mechanism. The results showed that the BiLSTM and hybrid deep learning CNN-BiLSTM models were able to produce high accuracy using the attention mechanism. The BiLSTM model with the attention layer achieves an accuracy of 84.25%, showing a 2.03% improvement over the baseline. On the other hand, the CNN-BiLSTM hybrid model reaches an accuracy of 83.01%, reflecting a 0.99% increase from the baseline. Although it does not always result in a large increase in accuracy, the attention mechanism can help depression detection from text data to be more accurate. There are limitations that need to be considered for future research. This analysis is limited by datasets from only one social media platform, X. Future research can analyze other social media platforms with different methods or algorithms.

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