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Confidence interval estimation of predicted values for the spread of COVID-19 using an ensemble approach

Kyulhee Han[1], Jiwon Park[1], Liu Zhe[1], Hanbyul Song[1], Xuwen Hu[2], Bogyeom Lee[3], Taesung Park[2*]

[1] *Interdisciplinary program of bioinformatics, Seoul National University, Seoul 08826, Korea.*

[2] *Department of Statistics, Seoul National University, Seoul 08826, Korea*

[3] *Department of Industrial Engineering, Seoul National University, Seoul 08826, Korea.*

**Corresponding author:* tspark@stats.snu.ac.kr

The spread of infectious diseases follows a complex pattern influenced by various factors. Accurately predicting these patterns is crucial for timely and effective intervention. Several predictive models exist, including statistical, mathematical, and deep learning models to predict patterns of spread. Some of these models, primarily statistical models, also provide confidence intervals for the prediction values in addition to point estimates. The confidence interval for prediction values has the advantage of providing additional information for the worst and best-case scenarios compared to simple point estimates. However, many models, especially deep learning models and ensemble models that integrate predictions from multiple models, often do not provide their own confidence intervals for prediction values. These models can provide confidence intervals for predictions based on the bootstrap method. Here, we use six individual prediction models (mathematical model: Extended SEIRD, statistical models: ARIMA, GAM, Time Series Poisson, machine learning models: Bi-LSTM, LightGBM) and three ensemble models (stacking, average, and weighted average) to provides confidence intervals for prediction values for COVID-19 daily confirmed cases in Korea. First, a total of 9 types of prediction results were used to generate bootstrap data (B=100) based on Moving Block Bootstrap (MBB) and Local Block Bootstrap (LBB) methods which are suitable for time series data. Each bootstrap data served as training data for each prediction model. Subsequently, we calculated the confidence intervals using the bootstrap data. Our findings revealed that ensemble models typically provided narrower prediction intervals than individual models. Additionally, confidence interval of ensemble models captured a higher number of true values compare to most individual models. Our findings highlight a commonly applicable methodology for deriving

confidence intervals across diverse prediction models, including both individual and ensemble approaches.