Supplementary Material

Table 1 describes the models submitted to the Centers for Disease Control and Prevention (CDC) for forecasting COVID-19 deaths.

Table 1: Overview of Category 1 models submitted to CDC for forecasting COVID-19 deaths, including their descriptions, categories, and estimation methods[1,2].

No.	Model	Description	Category	Estimation Method
1	Karlen[3]	The model employs discrete time difference equations with extended durations of a constant transmission rate.	Differential equations	-
2	MOBS[4]	The method segments the world into various geographical regions, each representing a distinct subpopulation. Human movement between these regions is represented as a network, with a data layer monitoring the number of people traveling between them. This mobility data is then used as the foundation for an agent-based epidemic model, which simulates the spread of infection and the dynamics of the global population.	Compartmental Model	Bayesian
3	PSI [5]	A stochastic SEIRX model. This predicts the statistical properties of possible outcomes by considering random variations in one or more parameters over time. The SEIR model is a compartmental model used to describe the spread of infectious diseases by dividing the population into four compartments: susceptible (S), exposed (E), infectious (I), and recovered (R). The SEIRX model builds upon the basic SEIR framework by potentially adding extra compartments or factors, such as quarantine or isolation measures (represented by 'X'), to more accurately reflect the complexities of disease transmission and control strategies within a stochastic setting.	Compartmental model	-
4	CovidComplete[6]	The forecasting method involves utilizing multiple models that use proxies, like positive test results and previous death counts, to estimate future deaths. The accuracy of each model is regularly evaluated, and models are selected weekly based on their past performance, with different models chosen for different states. Most forecasts are refined to correct errors identified in earlier predictions.	Statistical Learning	-

No.	Model	Description	Category	Estimation Method
5	UCSD-NEU[7]	This forecasting model combines the outputs of a discrete stochastic epidemic model, which employs a metapopulation approach (GLEAM), with a deep learning system that is designed to identify and correct spatial and temporal biases from previous predictions. The model assumes that current intervention strategies, like social distancing or travel restrictions, will continue when predicting future death tolls.	Deep Learning	-
6	Columbia [8]	This county-level SEIR model, based on a metapopulation approach, assumes that future contact rates will stay consistent with current levels. It provides estimates of spatio-temporal COVID-19 infections, hospitalizations, and deaths for all counties in the United States.	Compartmental model	Maximum Log-Likelihood
7	JHU-APL [9]	A spatial SEIR model designed to simulate COVID-19 at the county level utilizes public mobility data to construct the spatial compartmental framework.	Compartmental model	-
8	MIT-ORC [10]	This model forecasts future cases using a significantly modified SEIR model. It introduces new states to account for undetected cases and includes a specific state for deaths. The infection rate is adjusted with a nonlinear curve to reflect the evolving governmental and societal responses, which are assumed to vary with the severity of the outbreak. Key disease parameters are set based on a meta-analysis by the CovidAnalytics group, covering over 150 parameters, while epidemiological parameters are calibrated using historical death counts and detected cases.	Compartmental model	-
9	Bpagano[11]	A Death-based SIR model is employed to predict COVID-19 deaths and cases by examining historical changes in the virus's effective transmission rate. This model utilizes previous transmission data to forecast future outcomes.	Compartmental model	
10	UM[12]	This model uses ridge regression (penalized Ordinary Least Squares regression) to make predictions without depending on external assumptions. It employs Finite Impulse Response filtering to forecast daily confirmed cases based on the numbers from previous days.	Machine Learning	Bootstrapping

No.	Model	Description	Category	Estimation Method
11	ESG [13]	The model utilizes a skewed Gaussian distribution with four empirical parameters: height, position, left growth rate, and right decay rate. It operates without any epidemiological assumptions or parameters.	Statistical Learning	-
12	GT-DeepCOVID[14]	This data-driven deep learning model learns how hospitalization and mortality rates depend on various detailed factors, including syndromic, demographic, mobility, and clinical data (such as rising COVID-19 test positivity rates), based on historical data. The trained model is then used to forecast future mortality and hospitalization rates at different times. To mitigate the effects of noise in the data and initialization, the model is bootstrapped across multiple subsamples and then aggregated. Also, the model accounts for data uncertainties to provide confidence intervals in its forecasts.	Deep Learning	Bootstrapping
13	MIT-LCP [15]	This model uses a gradient-boosted regressor with hyperparameter optimization, utilizing prior COVID-19 cases and deaths along with demographic, socioeconomic, mobility, and healthcare-related county-level variables. It predicts COVID-19 deaths at the county level, which are then aggregated to provide state and national forecasts. While the model does not explicitly consider state reopenings and closures, it captures their effects indirectly through changes in mobility metrics.	Machine Learning	-

References

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