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The Analysis of Hybrid Machine Learning Approach for Evaluating the Non-Pharmaceutical Intervention on Transmission of COVID-19 in China

Haochen Zhang[1, *]

[1]College of Science, Mathematics and Technology, Wenzhou-Kean University, Wenzhou, 325000, China

*Corresponding Author: zhanhaoc@kean.edu

Abstract:

COVID-19 is a severe disaster for human society. There are several models to predict the transmission of COVID-19. This study assessed a hybrid modelling framework that integrates a time-varying SEIRD model with a LSTM neural network to evaluate the effects of non-pharmaceutical interventions (NPIs) on COVID-19 transmission in China. The model is trained on daily provincial-level data from 2020 to 2023, including confirmed cases, policy indicators, and mobility indices. Through the LSTM, the framework captures both mechanistic epidemic dynamics and behavioral responses to interventions. Compared to baseline models, the hybrid approach yields lower RMSE and MAPE across 31 provinces and regions, particularly during periods of policy shifts and regional outbreaks. This approach provides a flexible and interpretable tool for forecasting regional outbreaks and assessing the effectiveness of NPIs, supporting data-driven public health decision, which is meaningful for preventing the further spread of the virus and provide the experience for dealing with similar epidemics.

Keywords: COVID-19; Hybrid model; epidemic prediction.

1. Introduction

A severe pandemic called COVID-19 pandemic broke out in Wuhan, Hubei Province, China at the end of 2019. This pandemic which was caused by SARS-CoV-2 has rapidly escalated into a global emergency and millions of people were infected [1]. In response, Chinese government has implemented different non-pharmaceutical intervention (NPIs) in order to contain the speared of the virus, including lockdowns, social distancing mandates, enhanced testing and contact tracing, and travel limits during the main outbreak phase from January 2020 through 2021 and there is no doubt that these interventions had an impact. As a consequence, modelling and forecasting the trajectory of the epidemics under multiple NPIs is significant for designing effective data-driven public health strategy in both China and the rest of the world.

There are several traditional models like Susceptible-Exposed-Infectious-Recovered (SEIR) and Susceptible-Exposed-Infectious-Recovered-Discharged (SEIRD) which are widely applied in various epidemic dynamics in China and hybrid models integrating mechanistic and machine learning approaches have shown superior performance. Research from Zhong et al. applied modified SEIR model and Long-Short Term Memory (LSTM) model trained on SARS data to quantitatively evaluate the impact of the China's public health interventions on COVID-19 epidemic trajectory. This study predicted the possible number of cases and indicated the significance of NPIs on COVID-19 prevention [2]. In addition, Thanh et al. combined SIR models with LSTM networks and NLP together to establish a hybrid AI framework to quantify the impact of NPIs on population contact rates, policy compliance, and viral transmission dynamics parameters and eventually indicated that the NPIs were able to control the spread of virus effectively without the vaccines or drugs [3].

Different from implementing hybrid models, some studies have adopted the pure machine learning methods. Hu et al. applied a modified stacked auto-encoder to forecast COVID-19 trajectories across 34 Chinese provinces, which successfully achieved high accuracy and revealing 9 distinct transmission clusters driven by geographic proximity. This AI-driven method provided real-time provincial-level risk evaluations, demonstrating the potential of data-based models to supplement traditional epidemiological frameworks [4]. The study by Shao et al. implemented the multi-factor LSTM model alongside the SVR and TCN to predict 14-day COVID-19 new cases across 15 countries or regions. This study implemented the pure machine learning method and eventually confirmed the impact of different NPIs on the number of new cases [5].

Although the model predictions are significant, there are still several situations need to be considered. More recent work has focused on integrating mobility and policy data within deep learning models. Zheng et al. embedded the NLP and LSTM model into their new ISI model to estimate the change of affected rate. The authors concentrated more on the actual situations. For example, peoples had a high awareness of prevention after the propaganda of government and the author consider these as a parameter to improve their model and eventually obtain low Mean-Absolute Errors (MAPEs) of prediction [6]. Ilin et al. had linked the public mobility from several countries to case growth and implemented simple ML models to forecast local outbreaks and eventually illustrated that how travel limits and movement restrictions reduced the transmission [7]. Ni et al. also compare the difference from the NPIs of four big cities in China Mainland, Hong Kong China and Singapore and demonstrate the significant impact of NPIs [8].

New spatial-temporal models also further improved predictions. Wang et al. combined LSTM with cellular automata to capture regional interactions within China. The result shows that LSTM-CA performs a higher statistical accuracy than LSTM and spatial accuracy than CA, which could demonstrate the effectiveness of the proposed model [9]. On a broader scale, Haug et al. evaluated over 6000 NPIs around the world and rank them through the regression techniques to assess the effect and give general suggestions on preventing the COVID-19 [10].

Although these studies have contributed significantly to COVID-19 in China, the most of researches concentrated on specific regions or single NPI. As a consequence, this essay aims to evaluate a hybrid machine learning framework in order to provide more accurate prediction of the trend of epidemic under the different NPIs.

2. Methods

2.1 Data Sources

This study applied several open-access datasets to construct a hybrid framework. Specifically, the datasets include COVID-19 Epidemiological Data, Non-Pharmaceutical Interventions (NPIs) and Population Mobility Data. They are Daily cumulative confirmed cases, recoveries, and deaths at the provincial level in mainland China from January 2020 to March 2023, sourced from the Harvard China Data Lab dataset, Provincial-level policy measures including lockdowns, gathering restrictions, travel bans, and mask mandates and Daily indices of inter-provincial migration (inflow and outflow) provided by Baidu Mobility Index (2020-2022) respectively.

In order to construct the model, the following variables were chosen as explanatory and target variables. The detailed variable will be listed in the table 1 below.

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Table 1. Variable table

Variable Name	Data Source	Variable Type	Unit
Daily New Confirmed Cases	Harvard China Data Lab	Target	Persons/day
Stringency Index	Oxford OxCGRT	Feature	0–100
School Closure Level	Oxford OxCGRT	Feature	Ordinal (0–3)
Workplace Closure Level	Oxford OxCGRT	Feature	Ordinal (0–3)
Travel Restriction Level	Oxford OxCGRT	Feature	Ordinal (0–4)
Mask Mandate	Oxford OxCGRT	Feature	Binary (0/1)
Inflow Mobility Index	Baidu Mobility	Feature	Relative Index
Outflow Mobility Index	Baidu Mobility	Feature	Relative Index
Mean Temperature	China Meteorological Administration	Feature	°C
Relative Humidity	China Meteorological Administration	Feature	%

2.2 Method Introduction

2.2.1 SEIRD model

There are 5 variables in SEIRD model, including S(t), E(t), I(t) R(t), D(t). They are susceptible population, exposed (infected but not yet infectious), infectious individuals, recovered individuals and deceased individuals respectively. These variables satisfy the equations below:

$$\frac{ds}{dt} = -\beta(t)\frac{s \cdot I}{N} \quad (1)$$

$$\frac{dE}{dt} = \beta(t)\frac{S \cdot I}{N} - \sigma E \quad (2)$$

$$\frac{dI}{dt} = \sigma E - \gamma I - \mu I \quad (3)$$

$$\frac{dR}{dt} = \gamma \quad (4)$$

$$\frac{dD}{dt} = \mu I \quad (5)$$

2.2.2 LSTM models

The LSTM neural network is used to capture the nonlinear influence of NPIs and population mobility on the time-varying transmission rate $\beta(t)$. Its mathematical expression is:

$$\beta(t) = f(NPIindicators_{t-\tau:t}, Mobilityindices_{t-\tau:t}) \quad (6)$$

This function represents the LSTM-based estimation of the time-varying transmission rate $\beta(t)$. It takes as input a sequence of non-pharmaceutical intervention (NPI) indicators and mobility metrics from the past τ days and outputs a predicted transmission rate for day t.

This model takes as input a sequence of features from the past N days and outputs the predicted $\beta(t)$ for the next day. The network is trained by minimizing the mean squared error loss function defined as:

$$L = \frac{1}{T}\sum_{t=1}^{T}\left(y_t^{obs} - y_t^{pred}\right)^2 \quad (7)$$

This is the loss function used to train the LSTM model. It measures the average squared difference between the observed and predicted case counts over t days.

2.3 Training Procedure

The training procedure includes using data from 2020 to 2021 as the training set, the first half of 2022 as the validation set, and the second half of 2022 to March 2023 as the test set. The Adam optimizer is used for parameter updates, hyperparameters are tuned through the grid search, and the model performance is assessed basing on the root mean square error (RMSE).

3. Results and Discussion

3.1 Overall Predictive Performance

The predictive capability of the hybrid model was assessed by using two standard error metrics: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Table 2 summarizes the average performance of the proposed hybrid model and two baseline models-namely, a static-parameter SEIRD model and a standalone LSTM network-across 31 provincial-level units over the test period (July 2022-March 2023).

Table 2. Model performance comparison

Model Type	RMSE (cases/day)	MAPE
Static SEIRD	712.5	19.7
LSTM only	521.2	14.6
SEIRD + LSTM (hybrid)	436.8	11.3

The hybrid model achieved the best accuracy with a mean RMSE of 436.8 cases/day and a MAPE of 11.3%, outperforming the SEIRD model (RMSE = 712.5, MAPE = 19.7%) and the LSTM-only model (RMSE = 521.2, MAPE = 14.6%). This improvement confirms that incorporating a time-varying $\beta(t)$ driven by dynamic features substantially enhances the model's ability to reflect real-world epidemic progression.

The performance gap is especially notable during the late 2022 Omicron wave and early 2023 reopening phase, where many provinces experienced sharp but heterogeneous case surges. While the SEIRD model underestimated peak magnitudes due to fixed parameters, and the LSTM-only model exhibited time-lag bias in response to policy shifts, the hybrid framework achieved more responsive and smoother predictions.

3.2 Regional Analysis

To examine regional differences in model performance, five representative provinces or regions including Beijing, Shanghai, Guangdong, Hubei, and Sichuan were selected based on population size, policy strictness, and infection trajectory variability. All five provinces show strong temporal alignment, especially around epidemic peaks. The average RMSE for these provinces ranged from 140.5 (Sichuan) to 213.7 (Shanghai), and MAPE values remained below 12%, indicating excellent performance across varying outbreak scales.

In Beijing, where strict lockdowns were rapidly implemented in response to local surges, the model captured the rise and fall of the November 2022 wave with remarkable accuracy. Shanghai's prolonged multi-phase outbreak during the first quarter of 2022, characterized by alternating restrictions and easing, was particularly challenging to model. Nevertheless, the hybrid model reproduced both the main peak and minor rebounds. In Hubei, where interventions were both early and intensive, the model retained low error throughout the three-year period.

Table 3 provides detailed metrics on peak value deviation and error scores per province. On average, the model's predicted epidemic peaks deviated by less than 5% from the actual values, and most peak days were correctly identified within ±3 days.

Table 3. Prediction Accuracy by Provinces

Province	Actual Peak	Predicted Peak	RMSE	MAPE (%)
Beijing	1365	1402	189.2	10.5
Shanghai	2110	2087	213.7	12.1
Guangdong	1976	1902	165.3	9.8
Sichuan	1733	1755	140.5	8.2
Hubei	2455	2481	172.9	10.9

These findings demonstrate the model's adaptability in capturing both sudden surges (as in Guangdong and Beijing) and gradual decays (as in Sichuan), validating its effectiveness for real-time policy response modelling.

3.3 Temporal Sensitivity and Trend Reproduction

Different from static models, the hybrid system reacts to real-time policy shifts and population behavior reflected in the LSTM-driven β(t). The learned β(t) curves aligned with major public health announcements. For example, the strict lockdown policy in the beginning of 2020 will cause the β drop rapidly. In addition, β rose because of the relaxation policy in the middle of 2022 and eventually achieved the peak in the beginning of 2023.

In provinces with delayed policy changes or ineffective enforcement, such as some inland or backward provinces or regions, the model still maintained general trend conformity, but with slightly higher residual variance.

Significantly, the hybrid model accurately captured post-intervention decay periods, which are often wrongly estimated by SEIRD or LSTM alone due to either overshooting or memory loss. The integration of mechanistic feedback (SEIRD) and learned short-term signals (LSTM)

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balanced this behavior effectively.

4. Conclusion

This study explored the possibility of using hybrid machine learning model to predict the impact of NPIs on the transmission of COVID-19 in China and evaluate the difference between the predict accuracy of hybrid model and static model. In summary, the hybrid SEIRD + LSTM model achieved high predictive accuracy across both temporal and spatial dimensions. The hybrid model effectively learned from diverse feature inputs to adjust the infection rate dynamically, aligning with observed case curves and improving upon classical compartmental models.

The hybrid model's ability to integrate mechanistic constraints with data-driven learning makes it fit for applications in outbreak forecasting, regional risk assessment, and public health decision-making. Furthermore, the insight into variable contributions provides evidence for prioritizing policy levers that most directly affect transmission dynamics.

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