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SEIR Model Based Epidemic Transmission Risk Deep Prediction

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Abstract

Amidst ongoing efforts to manage the spread of infectious diseases, measures are taken to safeguard the resumption of on-campus activities. This ensures the academic continuity and the safety of the community. To achieve this, an analysis of disease transmission risks has been conducted, focusing on areas within campuses such as dining halls, lecture theaters, and classrooms. By leveraging an enhanced Susceptible-Exposed-Infectious-Removed (SEIR) model, we have developed a risk assessment model that takes into account dynamics between susceptible, latent, infected and displaced groups. After the extraction of relevant features, features undergo preprocessing steps. They are monotonically incremented and smoothed to eliminate noise, and then serve as input and labels for training stacked denoising autoencoder. The outcome of analysis indicates that the implementation of interventions can significantly mitigate the spread of disease. It can decrease the frequency of infection interactions, lower the transmission rate, and reduce the peak numbers of infected and latent cases by 61% and 72%, respectively. In essence, our approach has proven to be effective in controlling the spread of diseases in key university areas. Moreover, it provides an accurate predictive model for the number of infections, offering a valuable tool for managing and preventing outbreaks within these communities.

Keywords: Susceptible-Exposed-Infectious-Removed (SEIR) model, epidemic transmission, deep prediction model

1 Introduction

The coronavirus pandemic, known as COVID-19, is distinguished by its rapid spread, extensive reach, and the challenges it poses to containment and mitigation efforts (Abroon Qazi and Akram (2021); Moinet et al. (2018)). Until June 29, 2020, China had recorded 85,227 confirmed COVID-19 cases, with 4,648 fatalities and 80,055 individuals successfully recovering. With the situation now under more manageable control, there has been a gradual and structured return to normalcy in terms of work and production activities. Additionally, there is a growing demand for the reopening of colleges and universities.

However, unlike primary and secondary schools, universities and colleges have specific areas that are inherently prone to higher risk due to the dense population and close interactions among students and staff, such as dining halls, dormitories, and lecture buildings. These venues are hotspots for potential virus transmission. Should effective risk management and control strategies not be implemented, there is a significant risk of resurgence, which could lead to a rapid and widespread spread of the virus, potentially igniting another large-scale outbreak. Therefore, it is imperative that precautionary measures are stringently enforced to prevent such a scenario.

The National Health Commission and the Ministry of Education have published a technical guideline aimed at curbing the spread of infectious diseases within higher education institutions, highlighting the importance of focusing on areas within these establishments that are critical for disease control. Consequently, conducting a thorough risk assessment in these pivotal zones and devising targeted management and control strategies are essential steps towards facilitating a secure return for both academic staff and students, as well as ensuring the smooth and safe functioning of educational facilities.

The related works of epidemic risk analysis and management focus on the two core components: epidemic risk evaluation and epidemic risk propagation. For epidemic risk evaluation, Leitch et al. (2019) reviewed methods in predicting the thresholds of epidemic areas. Zhang et al. (2022) utilized spatio-temporal infected populations data in Wuhan before March 2020 to evaluate the influence of spatial distribution of urban facilities via generative adversarial networks predicting the infected risk. Kumar et al. (2024) proposed a SEIR-based evaluation model to predict the possible pandemic dynamics on daily COVID-19 case data in USA and main European countries, indicating that long-lasting moderate measures were better than rigid or loose ones. For epidemic risk propagation, Kudryashov et al. (2021) analyzed the propagation of the epidemic by refining the conventional SIR model. Chen et al. (2023) developed a toolkit for predicting the degree of epidemic risk propagation of COVID-19 in some high-income countries via multifactorial analysis. Li et al. (2024) established the equation of epidemic propagation and designed a threshold-based epidemic propagation model, which suggested promoting positive information and curbing negative information could help prevent epidemic risk propagation.

Nevertheless, the aforementioned studies seldom target the issue of resuming educational and work activities. Consequently, our research focuses on the critical areas within universities and colleges, taking into account that individuals in the latent phase can transmit the infection. We enhance the traditional SEIR model by incorporating this aspect and investigate the risk of campus-wide disease spread. To inform the development of epidemic prevention and control strategies in universities and colleges, we will also conduct a comparative analysis of various management and control strategies.

2 Method

2.1 SEIR Model

The SEIR (Susceptible-Exposed-Infectious-Removed) model is an advancement over the traditional SIR model by offering a partition of the population which consists of four distinct compartments (Zare and Vasegh (2021)):

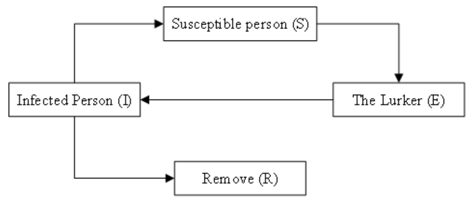

Figure 1: The transformation relationships among four distinct compartments in the SEIR model.

- Susceptible: This category includes individuals who are not infected with the disease and, due to lacking immunity, are at risk of contracting the infection upon contact with an infected person.
- Exposed: This category includes individuals who have been exposed to the infection but have not yet exhibited any symptoms of the disease.
- Infectious: This category includes individuals who have been infected and are capable of transmitting the disease to those who are susceptible.
- Removed: This category includes individuals who have either recovered from the illness or have succumbed to it, and thus are no longer part of the infectious cycle.

Figure 1 showcases the transformation relationships among four distinct compartments in the SEIR model.

Given S, E, I and R as the number of susceptible, exposed, infectious, and removed people in the population, respectively, the number transformation relationships among four distinct compartments over time obey the constraint $N = S + E + I + R$ and ordinary differential equations as follows:

$$\begin{aligned}
\frac{dS}{dt} &= -\beta_1 \frac{SI}{N} - \beta_2 \frac{SE}{N} \\
\frac{dE}{dt} &= \beta_1 \frac{SI}{N} + \beta_2 \frac{SE}{N} - \alpha E \\
\frac{dI}{dt} &= \alpha E - \gamma I \\
\frac{dR}{dt} &= \gamma I
\end{aligned} \tag{1}$$

In this paper, the SEIR model is deepened with the help of representations from stacked denoising autoencoder.

2.2 Stacked Denoising Autoencoder

Autoencoder (AE) networks are deep neural networks in unsupervised machine learning, which obtain higher-level representations of input data in an encoding-decoding manner. Typically, autoencoder networks need to keep output as same as input, i.e., recovering input.

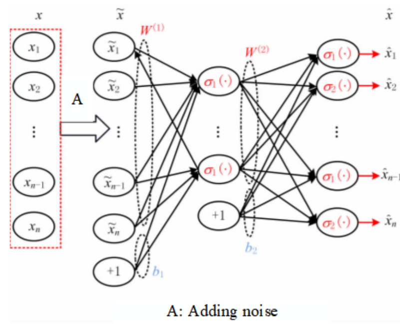

Figure 2: Denoising autoencoder.

Denoising Autoencoder (DAE) expands the function of autoencoder networks to the noise cancellation via replacing the recovering objective with denoising objective. As shown in Figure 2, DAE consists of an input layer, a hidden layer, and an output layer. The input layer and the hidden layer make up the encoder part of DAE, while the hidden layer and the output layer make up the decoder part of DAE. Before the input layer, noise is added into the origin data via process A. And the objective of the output layer is still the origin data. Consequently, DAE is tasked with learning to filter out the noise in order to reconstruct the clean input data. This requirement encourages the encoder part to develop a more resilient representation of the input dat, thereby enhancing its capacity to generalize beyond the training data.

Given clean dataset $X = x_1, x_2, \cdots, x_n$, the input dataset after process A (adding noise) is $\tilde{X} = \tilde{x_1}, \tilde{x_2}, \cdots, \tilde{x_n}$. The weight and bias of the encoder part are $W^{(1)}$ and b_1, respectively. Similarly, the weight and bias of the decoder part are $W^{(2)}$ and b_2, respectively. The computation in the encoder part is:

$$h = \sigma_1(W_1\tilde{x} + b_1). \tag{2}$$

where σ_1 is the activation function in the encoder part, and h is the representation in the hidden layer. The computation in the decoder part is:

$$\hat{x} = \sigma_2(W_2 h + b_2). \tag{3}$$

where σ_2 is the activation function in the decoder part, and $\hat{x}$ is the reconstructed clean data in the output layer.

Stacked autoencoder combines multiple autoencoder networks to form a deeper network via connecting each encoder part and then each decoder part. Its training process obeys the rule of “from shallow to deep”. That is, first, training the shallow encoder part and the shallow decoder part, then, training the deeper encoder part and the deeper decoder part. This manner makes decoder and more general representations can be obtained.

In this paper, general representations from stacked denoising autoencoder are used to predict the development of epidemic in the SEIR model.

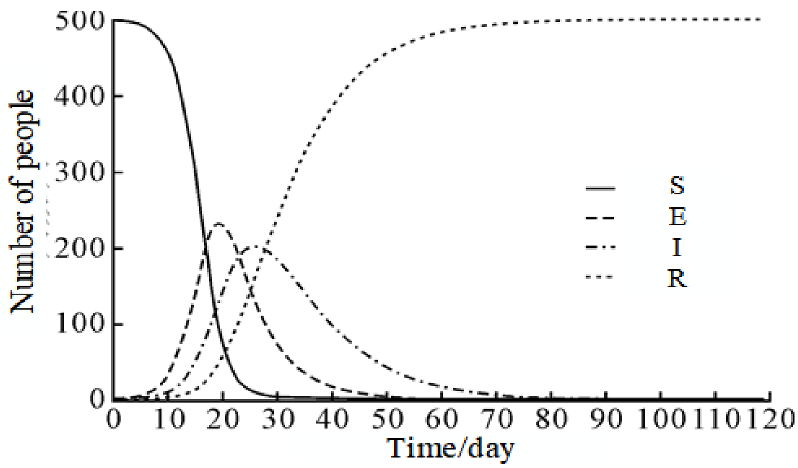

Figure 3: Epidemic propagation without implementing control strategies.

3 Experiments

A specific university was chosen for our study, and MATLAB was used to implement the stacked denoising autoencoder and the enhanced SEIR model. That university consists of 35,000 undergraduates, 15,000 master's students, 2,000 doctoral candidates, 1,500 international students, and 5,000 staff members. The campus includes common areas that are typically bustling with activity, such as lecture halls, dormitories, cafeterias, and auditoriums.

Without implementing any control strategies, the dining hall accommodates 500 individuals per mealtime, including individuals who are already infected. We start with an initial count of 2 infected individuals. The epidemic propagation over a 120-day period is shown in Figure 3. According to Figure 3, the infection peak occurred around the 25th day, with the highest recorded number of infected individuals surpassing 200.

Control strategies include off-peak dining and social distancing to minimize gatherings, wearing masks and keeping hand hygiene to reduce interpersonal propagations, and disinfection to further decrease the infection rate. These strategies can effectively halve the daily interactions between infected and susceptible individuals, and reduce the infection rate by one-third. The epidemic propagation over a 120-day period under control strategies is shown in Figure 4. According to Figure 4, the impact of these control strategies is significant. The infection peak is delayed to around the 75th day, with the number of infected individuals at the peak significantly reduced to about 80.

According to the comparison between Figure 1 and Figure 2, the efficacy of control measures in critical areas of universities and colleges can be found. In the absence of any control measures, epidemic propagation is in an exponential-like manner. Once control measures are implemented, there is a significant reduction in the frequency of interactions between infected and those individuals, which leads to a decrease in the per-contact transmission rate, effectively reducing the epidemic propagation. Consequently, the peak numbers of infected individuals are reduced by 61%, demonstrating the substantial benefits of these control strategies.

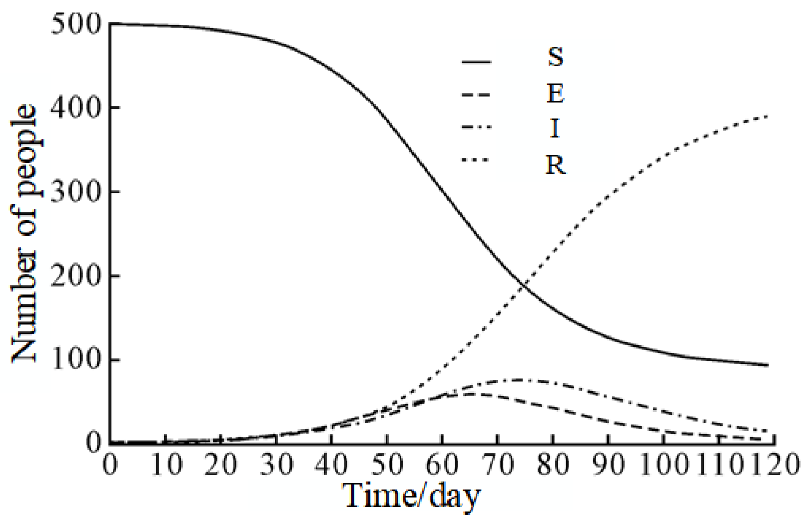

Figure 4: Epidemic propagation with implementing control strategies.

4 Conclusion

Amidst the background of universities resumption under a framework of sustained epidemic prevention and control, this study focuses on the potential risks of epidemic propagation within pivotal campus settings such as dining halls, auditoriums, lecture buildings, and dormitories. Drawing from an enhanced SEIR model tailored to these areas, strategies for mitigating risks in these critical zones have been proposed. Nevertheless, because the epidemic propagation is influenced by a multitude of variables, the precision of our method remains unperfect. In the future, we plan to incorporate more sophisticated deep learning techniques to enhance the accuracy of our forecasts.

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