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A simple mathematical model to predict short-term trends and to suggest preventive measures to control the spread of an infection during a pandemic

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Abstract*— On January 3, 2020, Chinese health officials identified an outbreak of pneumonia in the Chinese city of Wuhan. The virus swiftly spread to the majority of countries, infecting a substantial portion of the population. On September 28, 2020, reports of nearly a million deaths were made globally. Every day, huge amounts of data were gathered, and data analytics became crucial for identifying patterns and identifying how the infection spread. Numerous predictive models were employed to assess the impact of non-pharmaceutical interventions (NPIs) on the spread of SARS-CoV-2. Some of the models also predicted daily new cases and mortality patterns. The SEIR model is one of many that were employed. The SEIR approach calculates the end results using differential equations and requires other programming language skills to visualize the results, making it difficult for ordinary people to use predictive model. We created a basic mathematical model that is straightforward to apply, and the results show that it is successful in controlling pandemic spread. The proposed approach employs a predefined set of logics that are deployed in accordance with current developments. The present trend is established by comparing the volume of instances recorded in 7 days with the volume recorded in the previous 7 days. This model is used to forecast short- term trends, and the pre-defined set of logic advises appropriate actions to restrict illness spread during a pandemic.

Index Terms*— Infectious disease, non-pharmaceutical interventions, pandemic, predictive model.

I. INTRODUCTION

The Chinese city of Wuhan was the site of the first detection of the COVID-19 pandemic in January 2020. In a short amount of time, the virus spread to nearly every region on Earth. Lockdowns, travel bands, stay at home, isolation, hand hygiene, and face masks were among the control methods employed to slow down the pandemic's spread. Almost 7 million individuals had passed away by the end of September 2023. Numerous nations' economies were devastated by COVID-19. Countries like Bangladesh, Pakistan, and Sri Lanka are a couple of such instances. The illness has resulted in fresh advancements every three months since its first detection. Thousands of demonstrators on the streets of China, India, and the United States of America pressured government authorities to ease restrictions. As a result, the infection and mortality rates increased. In the most developed countries, hospitals were overflowing with patients, and dead bodies were found lying on the streets, ready to be buried. It took nearly two years for the situation to improve globally. Every country has learned the value of pandemic preparedness as a result of the COVID-19 pandemic.

During the COVID-19 epidemic, predictive models such as SEIR, ARIMA, and automated time series machine learning algorithms were employed to forecast future trends. The majority of the model's predictions and recommendations failed to stop the virus from spreading. Recent days have witnessed an overwhelming amount of criticism focused on model projections and the wildly varied forecasts regarding the number of coronavirus illnesses [1]. After looking into what caused these models to fail, we found that underreporting of cases, inaccurate data, and effective government actions to restrict spreading are the main causes of the difference in projections [2]. Furthermore, there is a great deal of complexity involved in understanding and employing these models. It requires advanced mathematical knowledge, as it uses ordinary differential equations and knowledge of programming languages like R or Python to visualize the output. The objective of this study is to develop a simple mathematical model to predict short-term trends and to suggest optimal measures to control the spread of infections during a pandemic. The proposed model is named the *IRP model*, as this model helps in identifying the infectiousness of the disease, recommends NPIs, and predicts values required for forecasting.

II. BACKGROUND

Numerous computational and mathematical models were employed throughout the pandemic to predict the daily number of new cases and fatalities. The majority of the forecasts failed, and the model's predictions were widely criticized. Moreover, the following list describes the challenges of using predictive models.

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A. Complex nature

A simple epidemic model called the SIR model estimates the number of infectious disease cases that could develop over time in a closed community. The compartment model typically consists of three boxes that divide the population into multiple separate groups.

S - People that are susceptible to the epidemic.

I – Already infected people who can spread the disease to the S.

R - People that are recuperated or deceased [3].

The SIR model detailed here is the most basic model used to forecast new cases every day throughout the pandemic. The simplest model is perhaps the most difficult for regular people to comprehend. From an individual understanding standpoint, the fundamental ideas and ODEs (ordinary differential equations) employed are radical.

B. Duration of model construction and testing

Building a dependable model takes longer than six months. Analyzing and defining the goals prior to model construction necessitates extensive debate. In order to complete the process, a number of steps must be completed, including locating sources of data, selecting pertinent data for analysis, pre-processing the data, figuring out a methodology, and creating the model. The model is then tested using test data, and the results are verified using real data.

C. Associated costs

Developing predictive computational models is incredibly expensive. There are two different kinds of costs involved. One is the price of hiring knowledgeable data scientists to create and evaluate a model. The second is the expense of configuring the environment in which the model runs.

D. Skills required

These models require sophisticated computational and mathematical knowledge to construct and run. Among the skills are knowledge of differential calculus, experience with data collection and preparation, familiarity with the R and Python programming languages, etc.

To overcome these challenges, we have proposed the IRP model.

III. METHODS

The proposed model is experimental and uses quantitative methods to solve the issue. It also uses simple mathematical formulas to calculate the volume of cases, the change in volume of cases, and to predict future trends. The proposed model uses the data gathered for a period of 7 days and iterates through many cycles until the infectious disease is contained. This model has the ability to predict short-term trends. A set of pre-defined logical assumptions is used to predict trends and suggest optimal interventions to control the spread of the infection. This approach may be used to track and control illnesses that have originated in the nation or have been imported from other countries. The proposed model consists of five phases and each phase of this model is explained using illustrations.

IV. THEORY / CALCULATIONS

The infectious disease in this model progresses through multiple phases. Below is a discussion of this model's several phases.

Infection Discovery Phase

- A new infection is identified.
- The infection is monitored for a period of 7 days to identify similar infections in the population.
- The total volume of cases identified is calculated on the 7th day from the day of infection discovery.
- The observation recorded is plotted using a line chart.

Illustration

Figure [1] explains the first iteration.

Total number of cases recorded: 2715.

Observations	New cases
1	1
2	4
3	70
4	250
5	490
6	660
7	700

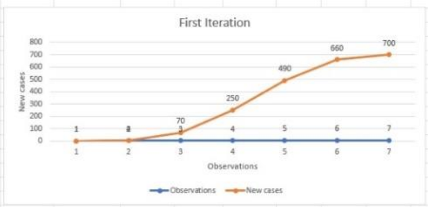

Figure 1: Discovery Phase

Observation Phase

- The infection is closely observed for the next seven days.
- The total volume of cases identified is calculated on the 7th day.
- The observation recorded is plotted using a line chart.
- The change in volume of cases is identified by calculating the difference in the volume of cases recorded in the last two iterations.
- The initial forecast for the next 7 days is created by adding the per-day increase to the daily observations recorded in the last iteration.
- The percentage increase is calculated using this formula [Final Value - Starting Value / Starting Value] * 100.
- If the increase is above 10%, the decision phase is initiated.

Illustration

Figure [2] explains the second iteration.

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Observations	New cases
1	580
2	690
3	700
4	430
5	750
6	890
7	1100

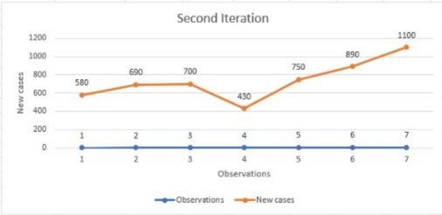

Figure 2: Observation Phase

Total volume of cases recorded: 5,140.
Change in volume of cases: 5,140 - 2,715 = 2,425
Per-day increase 2425 /7= 346 (rounded off)
Percentage Increase: [5,140 - 2,715 / 2,715] * 100= 89.3%

Figure [3] shows the initial forecast.

Observations	New cases	Per day increase	Forecast
1	580	346	926
2	690	346	1036
3	700	346	1046
4	430	346	776
5	750	346	1096
6	890	346	1236
7	1100	346	1446

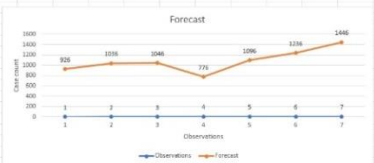

Figure 3: Initial forecast

Decision Phase

- In this phase, based on the increase in the percentage of new cases, a decision is made to select a set of suitable actions from the xAUS table shown in figure [4] to control the spread of infection.
- The xAUS table parameters are derived from real-time pandemic scenarios. Each parameter is assigned a value. The values of these parameters shown in figure [5] are determined based on their ability to control the spread of infection during a pandemic.
- After selecting the logic, predictions based on the xAUS table are plotted using line charts for the next 6 iterations, each with an observation for 7 days.
- Post-implementation, the situation is monitored for another 7 days, and the volume of cases recorded is calculated on the 7th day.

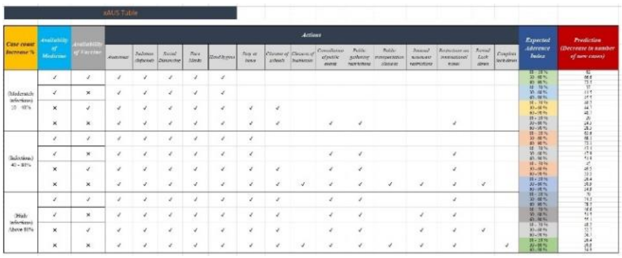

Figure 4: xAUS Table

Weightage

S.No	Parameters	Number of items/Scale	Weightage
1	Availability of Medicine		25
2	Availability of Vaccine		25
3	Actions	Each	1.6
4	Expected Aderence Index	10 - 30 30-60 60-90	4 8.5 12.5

Figure 5: xAUS parameter values

Illustration

Figure [6] shows the selection criteria based on the case increase percentage.

xAUS Table

Case count Increase %	Availabilty of Medicine	Availability of Vaccine	Awareness	Isolation (Infected)	Social Distancing	Face Masks	Hand hygine	Stay- hom
(Moderately Infectious) 10 - 40%	✓	✓	✓	✓	✓	✓	✓	
	✓	×	✓	✓	✓	✓	✓	
	×	✓	✓	✓	✓	✓	✓	✓
	×	×	✓	✓	✓	✓	✓	✓
(Infectious) 40 - 80%	✓	✓	✓	✓	✓	✓	✓	✓
	✓	×	✓	✓	✓	✓	✓	✓
	×	✓	✓	✓	✓	✓	✓	✓
	×	×	✓	✓	✓	✓	✓	✓
(Higly Infectious) Above 80%	✓	✓	✓	✓	✓	✓	✓	✓
	✓	×	✓	✓	✓	✓	✓	✓
	×	✓	✓	✓	✓	✓	✓	✓
	×	×	✓	✓	✓	✓	✓	✓

Figure 6: xAUS - Infection classification

At this point, the percentage increase in new cases is identified as 89.3%. From the table, we can confirm that it is a highly infectious disease, and based on the availability of medicine and vaccines, an appropriate set of actions is selected. For the purpose of illustration, we have considered the availability of medicine as "yes" and the availability of vaccines as "no".

Figure [7] shows the selected logic with recommended actions.

Figure 7: xAUS - Recommended actions

Raising awareness, isolating the affected, social distancing, wearing face masks, practicing good hand hygiene, staying at home, closing schools, calling off public events, imposing

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limitations on gatherings in public, limiting internal travel, and restricting travel outside are a few of the measures. The user will be required to select the expected adherence index after choosing the recommended actions. For each recommended set of actions, the expected adherence index (EAI) levels are displayed in Figure [8]. EAI depends on the stringency score. We take the projected adherence index to be between 30 and 60% for the purpose of illustration.

plete down	Expected Aderence Index	Prediction (Decrease in number of new cases)
	10 - 30 %	62
	30 - 60 %	66.6
	60 - 90 %	72.5
	10 - 30 %	37
	30 - 60 %	41.5
	60 - 90 %	45.5
	10 - 30 %	40.2
	30 - 60 %	44.7
	60 - 90 %	48.7
	10 - 30 %	20
	30 - 60 %	24.5
	60 - 90 %	28.5
	10 - 30 %	63.6
	30 - 60 %	68.1
	60 - 90 %	72.1
	10 - 30 %	43.4
	30 - 60 %	47.9
	60 - 90 %	51.9
	10 - 30 %	45
	30 - 60 %	49.5
	60 - 90 %	53.5
	10 - 30 %	26.4
	30 - 60 %	30.9
	60 - 90 %	34.9
	10 - 30 %	70
	30 - 60 %	74.5
	60 - 90 %	78.5
	10 - 30 %	46.6
	30 - 60 %	51.5
	60 - 90 %	55.1
	10 - 30 %	48.2
	30 - 60 %	52.7
	60 - 90 %	56.7
	10 - 30 %	26.4
	30 - 60 %	30.9
	60 - 90 %	34.9

Figure 8: xAUS EAI

Predictions Phase

- Using the prediction values listed in the xAUS table, we may forecast the new cases for the following iteration after assuming the EAI value. The model forecasts a 51.5% drop in the number of new instances in the following iteration in this example.
- Based on the prediction values found in the xAUS table, the original projected values from the *observation phase* will be updated with new values.
- Forecasts are made for the next six cycles.
- Line charts are created to visually present the data.

Illustration

Based on the values anticipated by the model, the forecast for the following six iterations can be seen in Figure [9]. The original values predicted during the *observation phase* are adjusted with these values.

Observations	Initial forecast	First set	Second set	Third set	Fourth set	Fifth set	Sixth set
1	926	477	246	126	65	34	17
2	1036	534	275	142	73	38	19
3	1046	539	277	143	74	38	20
4	776	400	206	106	55	28	14
5	1096	564	291	150	77	40	20
6	1236	637	328	169	87	45	23
7	1446	745	384	198	102	52	27

Figure 9: Forecast for next 6 iterations.

Figure [10] shows the line chart of the forecast for the next six iterations.

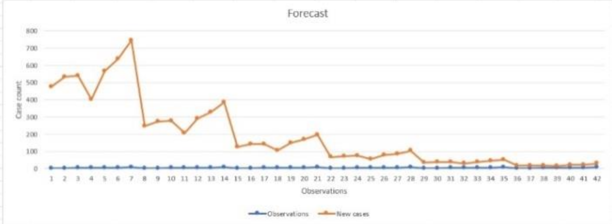

Figure 10: Forecast - Line chart

Monitoring Phase

- During the next seven days, the situation is observed, and daily case reports are made.
- Compare this cycle's outcomes with the prediction plots made with the xAUS table.
- If the data show a drop in the number of cases, use the same procedure for the remaining iterations until the infection is under control.
- An examination of the EAI is done if the outcome is negative; if the EAI is met, a decision phase is started, and a new set of logic is chosen. The updated forecast based on the xAUS table is plotted for the next six iterations, each with a seven-day observation period, based on the suggestions of this logic and non-pharmaceutical interventions.
- If the EAI is not met, select a lower EAI score, plot the forecast for the next six iterations, and repeat the process until the volume of new cases decreases.

V. RESULTS

The simplicity and ease of implementation of the approach can be readily observed from the illustration above. Prescriptive and predictive analytics are two ideas that are used in this strategy. The optimal combination of NPIs to stop the pandemic from spreading is suggested after analyzing all the variables that contribute to the infection's propagation within the population. Neither advanced mathematical understanding nor programming experience are needed to use this concept. In the near future, this very basic model has the potential to develop into a highly advanced model.

VI. DISCUSSION

The xAUS table is an assumption-based table. These presumptions can be useful in the management of different types infectious diseases. In order to increase its forecasting accuracy, we occasionally need to make adjustments to some of the variables and assumptions that are applied to it.

VII. CONCLUSION

This is a simple mathematical model to predict short-term future trends. This model can be used to control the spread of different types of infectious diseases. This model also helps in infection discovery and tracks the status of all the

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infections until they are completely removed. The cost involved in implementing this model is very low when compared to other models. This model also relies on the quality and accuracy of the collected data. This model relies on manual input of data and calculations. Eventually, automation software will be able to automate this concept.

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