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Covid-19 Endogenous Mutation Of Nb 1.8.1, Lf.7 And Kp.3: Applying A Multivariate Time-Series Model To Forecast Key Healthcare Indicators Through 2027

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Abstract
Following the extensive devastation wrought by the global COVID-19 pandemic, the emergence of novel mutations persists on an international scale. The enduring impact of these mutations on public health infrastructure constitutes a matter of significant concern. Covid-19 variants NB.1.8.1, LF.7 and KP.3, both classified as Variants Under Monitoring (VUMs) by the World Health Organization, have been isolated in global wide. These variants highlight the ongoing evolution of SARS-CoV-2 and the need for continuous genomic surveillance to monitor their spread and impact on public health. It is difficult to determine the specific health complications they face, but observations from affected areas suggest certain patterns. This paper presents a long-term forecasting analysis of three crucial healthcare indicators—Daily New Deaths per Million, Hospital Patients per Million, and Test Positivity Rate—using time series models based on the Prophet algorithm. The analysis draws on data from multiple countries with varying healthcare dynamics and pandemic response strategies. Forecasts extend through 2027, offering insights into potential healthcare burdens and seasonal trends in an endemic COVID-19 landscape. The results demonstrate divergent trajectories among nations and highlight the value of data-driven health policy planning.
Keywords: *COVID-19, Health forecast, Mutation, variant NB 1.8.1, LF.7, KP.3, Time-series etc.*

1. INTRODUCTION

Since its inception in late 2019, the SARS-CoV-2 virus, which is the causative agent of COVID-19, has demonstrated an extraordinary capacity for evolution, resulting in the emergence of multiple variants characterized by unique genetic, phenotypic, and epidemiological traits[1-4]. Although initial apprehensions were primarily directed towards the Alpha, Beta, Delta, and Omicron strains, the virus has persistently adapted in response to immunological pressures, demographic dynamics, and public health measures [5-7]. By the year 2024, focus had transitioned to newly identified subvariants such as NB 1.8.1, LF.7, and KP.3, which display endogenous mutations—evolutionary changes that transpire within a particular population or geographic area, independently of the introduction of exogenous variants [8,9]. The escalating prevalence and transmission of these endogenously mutated variants are inciting renewed concerns within the public health domain [10, 11]. In contrast to previous waves during which vaccination initiatives and natural immunity provided substantial protective advantages, the latest lineages seem to partially circumvent established immunity, resulting in unprecedented patterns of morbidity, hospitalization, and strain on healthcare systems [12-15]. Significantly, NB 1.8.1 has exhibited heightened transmissibility and prolonged viral persistence within upper respiratory tissues, whereas LF.7 is associated with increased rates of reinfection and diminished effectiveness of neutralizing antibodies [16]. KP.3, a recombinant subvariant, has displayed moderate severity but markedly elevated rates of breakthrough infections among individuals who have been vaccinated [17, 18].

The figure.1 unequivocally presents the data collected by the World Health Organization (WHO) regarding the number of COVID-19 cases reported worldwide for the week concluding on 11 May 2025. A staggering total of 74,645 cases was reported during this timeframe, indicating a remarkable increase of 69,149 cases in comparison to the preceding week. A global map decisively illustrates the distribution of cases across various WHO regions, with a pronounced concentration evident in the South-East Asia region, distinctly marked in green.

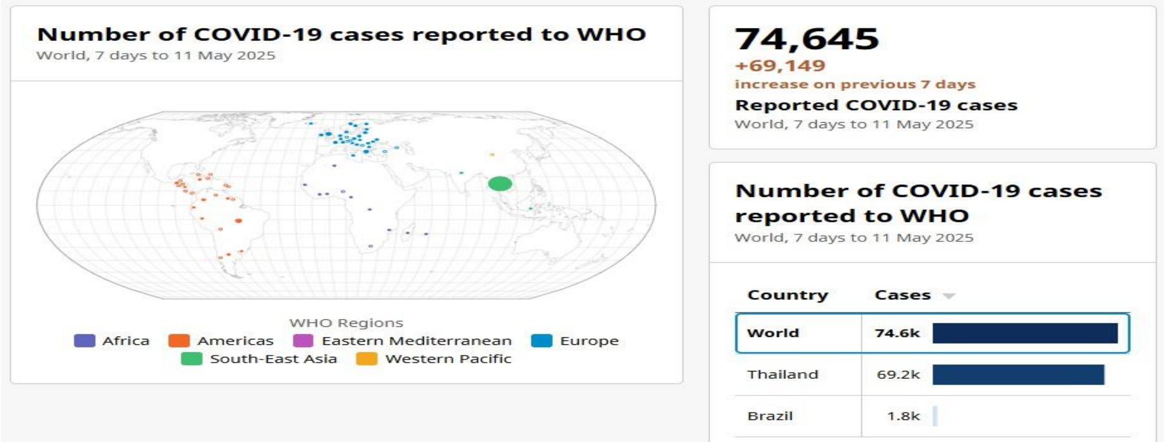

Figure.1 COVID-19 First week of May 2025 (7days)
(Sources from WHO)

In the figure.2 categorically displays the cumulative total of COVID-19 cases reported to the World Health Organization (WHO) as of 11 May 2025. The global total has escalated to 777,825,189 cases, with an increase of 74,645 cases during the most recent 7-day reporting period. A world map systematically illustrates the distribution of cases across WHO regions, utilizing distinct colors to represent Africa, the Americas, Eastern Mediterranean, Europe, South-East Asia, and Western Pacific. The map prominently highlights a dense concentration of cases in Europe and the Americas.

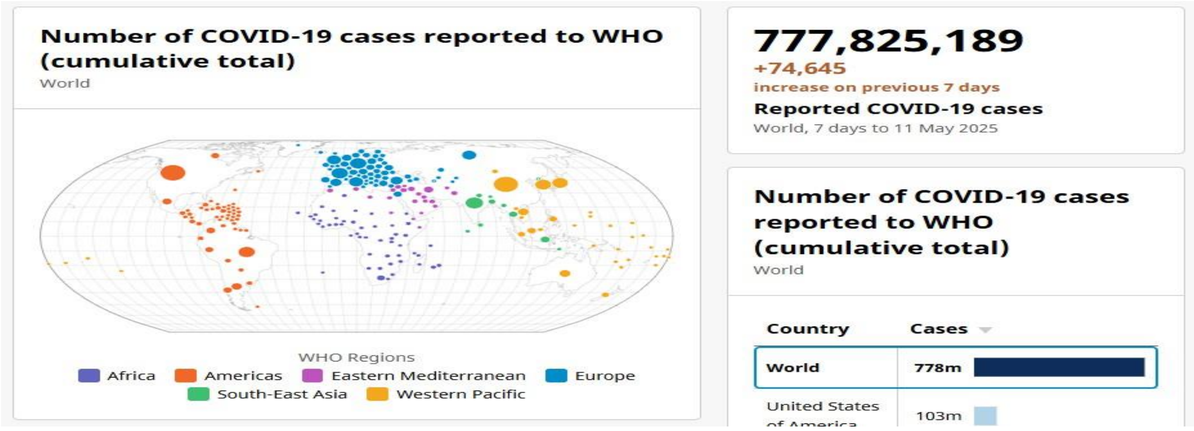

Figure.2 COVID-19 cases as of May 2025
(Sources from WHO)

In light of this continuously evolving virological landscape, healthcare systems are confronted with the dual challenge of addressing current demands while simultaneously preparing for prospective surges [19-21]. Anticipating critical healthcare indicators—such as hospitalization rates, intensive care unit (ICU) occupancy, mortality trends, and dynamics of vaccine efficacy—necessitates the application of models that extend beyond simplistic trend analysis. Within this framework, multivariate time-series models present a robust methodology, facilitating the simultaneous examination of interdependent variables over time, while integrating both direct epidemiological metrics and broader healthcare system indicators [22-26]. This research article integrates of multiple correlated indicators, such as the prevalence of variants, hospitalization rates, and vaccination uptake, within a cohesive framework. Secondly, such models are capable of capturing dynamic interrelationships and lag effects that are frequently neglected by univariate models, including the delayed repercussions of variant emergence on ICU admissions. Thirdly, a properly specified multivariate model enhances predictive capabilities, equipping policymakers to anticipate stress points within the healthcare system under various mutation and transmission scenarios [27-30]. Since 2019, major COVID-19 variants include Alpha, Beta, Gamma, Delta, Omicron (with subvariants like BA.2, BA.4, BA.5, XBB, and EG.5), each showing varying transmissibility and severity. New variants continue to emerge due to viral mutations and global transmission. Forecasting is essential to anticipate healthcare burdens, guide vaccination strategies, and prepare for seasonal or unexpected surges.

Table 1. List of COVID-19 Variant

Variant Name	Lineage	WHO Classification	Key Mutations	Year Identified	Origin
XBB.1.5	Omicron recombinant	VOI	F486P, S486P	Late 2022	USA
JN.1	Omicron sublineage	VOI	L455S, others	August 2023	France
NB.1.8.1	JN.1 descendant	VUM	Unknown (Omicron lineage)	2024	Asia
LF.7	BA.2 sublineage	VUM	Unknown	2024	India
KP.3	Omicron sublineage	VUM	F456L, Q493E	2024	Global

The above table.1 consist of variants (2023-25) based on their public health significance, including variants of concern, variants of interest, and variants under monitoring. This study builds upon existing genomic surveillance, public health data, and health informatics systems to formulate a forecasting model designed to inform both national and regional healthcare strategies through the year 2027.

This research article is composed of seven distinct sections. The introduction section furnishes a comprehensive overview of the research focuses. In the second section, recent scholarly articles are reviewed that underscore significant findings and methodologies pertinent to the study. The third section delineates the objective of the research. In the fourth section, a methodology is proposed that encompasses a systematic model for assessing the effectiveness of COVID-19 mutations and their implications for public health strategies. In the fifth section, we analyze the results derived from the proposed model. In the sixth section, we deliberate on the implications of our findings for future public health interventions. The final section concludes the article by summarizing the principal insights gained from the research.

2. LITERATURE REVIEW

Dr. Saeed Q Al-Khalidi Al-Maliki, Dr. Prakash Kuppuswamy, Dr. Rajan John, and Dr. Nithya Rekha Sivakumar (2022) assert that their research endeavors aim to scrutinize the extent of mutations in COVID-19 and assess its vulnerabilities. The authors employed the J48 algorithm alongside the Linear Regression algorithm. The findings will significantly aid clinicians and medical researchers in grasping the nuances of COVID-19 variant mutations across various phases. Artificial intelligence-driven algorithms facilitate a superior understanding of the stages of COVID-19 and the corresponding vulnerability levels. In this pandemic context, artificial intelligence stands as an indispensable asset for healthcare operations. Nevertheless, the implementation of machine learning-based methodologies articulated in this article will enable swifter and more proactive diagnoses of any prospective pandemic scenarios in the future [30].

Prakash Kuppuswamy, Sayed QY Al Khalidi, and Vijaya Varshini Prakash (2024) contend that predictive analytics has emerged as an authoritative force in healthcare, fundamentally transforming our approach to patient care, disease prevention, and resource management. This field encompasses advanced data analysis techniques that forecast future outcomes and trends based on historical data, empowering healthcare providers to make astute decisions and undertake proactive initiatives. In this article, we will thoroughly examine the application of prediction algorithms in disease prevention and early detection, their advantages, challenges, and best practices; we will also delve into the realm of predictive analytics tools and methodologies, investigating their capabilities, benefits, and best practices in healthcare, along with their escalating significance in contemporary society [31].

Xinyi Yang et al. (2023) Still COVID-19 has emerged as a challenging to the global healthcare, creating a challenges to antimicrobial stewardship on global. This article suggests a meticulous and contemporary analysis of global antibiotic utilization among COVID-19 affected people. This article aimed at measuring the prevalence of antimicrobial resistance (AMR) and antibiotic application among COVID-19 affected people undergoing treatment in healthcare institutions. The findings from the meta-regression unequivocally identified antibiotic use and intensive care unit (ICU) admission as significant predictors correlating with an elevated prevalence of MDROs in COVID-19 patients. [32].

Català, Martí (2025). This article evaluate the overall effectiveness of vaccination in averting long COVID symptoms and to assess the comparative effectiveness of the most widely administered vaccines. The research employed a staggered cohort study utilizing primary care records from the UK, the Catalonia, and the Spain Information System for Research in Primary Care, alongside national health insurance claims from Estonia. Individuals who received vaccinations were further categorized by vaccine brand based on the initial dose administered. The primary outcome for long COVID was precisely defined WHO-listed symptoms occurring between 90 and 365 days post PCR-positive test or clinical diagnosis of COVID-19, with no prior history of that symptom within 180 days preceding SARS-CoV-2 infection. Widespread random effects meta-analyses across staggered cohorts were conducted to cumulative effect. Due to the Vaccination, COVID-19 consistently reducing the long-term COVID-19 problems [33].

Akingbola A (2025) declares that vaccination has played a pivotal role in mitigating the transmission of SARS-CoV-2 and alleviating the severity of clinical manifestations associated with COVID-19. A plethora of COVID-19 vaccines have been developed for this purpose, including BioNTech-Pfizer and Moderna's mRNA vaccines, as well as adenovirus vector-based vaccines such as Oxford–AstraZeneca. Nevertheless, the emergence of novel variants and subvariants of SARS-CoV-2, characterized by heightened transmissibility and immune evasion capabilities, presents substantial challenges to the effectiveness of existing vaccination strategies. In this review, we aim to provide a comprehensive overview of the evolving landscape of emerging SARS-CoV-2 variants of concern (VOCs) and sub-lineages that have recently emerged in the post-pandemic landscape. Moreover, innovative adjuvants that activate dendritic cells, stimulate cytokine secretion, and facilitate cross-presentation to CD8+ T cells can significantly enhance cellular responses and establish long-lasting immunity. Additionally, the adoption of cutting-edge delivery systems such as nanoparticles or exosome-like vehicles enhances antigen presentation, lymph node targeting, and promotes more effective adaptive immune priming. While traditional platforms, such as live attenuated and inactivated vaccines, provide robust and enduring humoral and cellular immune responses, they are accompanied by safety and logistical challenges that must be addressed [34].

Dr. Prakash Kuppuswamy, Dr. Saroj K. Gupta, Dr. Indhu Sharma, Dr. Saeed Q. Y Al Khalidi Al-Maliki, Ahmed Ali ShaikMeeran, and Ahmed Hamed (2024) the research aims to meticulously investigate prospective pandemic scenarios and their associated vulnerabilities. By embracing the machine learning-based methodologies delineated in this research, healthcare operations can promptly and effectively recognize potential pandemic scenarios. Linear regression serves as a statistical approach to forecast the value of one variable in relation to another. The results demonstrate comparable prediction accuracy. The Support Vector Machine (SVM) exhibits identical MSE and R-squared values as the Random Forest, reflecting equivalent performance. The Random Forest method is acknowledged for yielding superior predictions based on dataset trends. Critical elements influencing the timeline and repercussions of pandemics encompass population density, climate, economic activity, healthcare resources, preventive measures, historical data, global travel, and the efficacy of pandemic models. A holistic approach that integrates these factors is essential for robust preparedness and response strategies in the future [35].

3. RESEARCH OBJECTIVES

The primary objective of this investigation is to formulate and validate a model capable of accurately predicting essential healthcare indicators in response to the endogenous evolution of the NB 1.8.1, LF.7, and KP.3 variants of COVID-19. The analysis will encompass the genomic characteristics and mutation patterns of the NB 1.8.1, LF.7, and KP.3 variants, with an emphasis on elucidating how endogenous mutations influence alterations in transmission dynamics, immune evasion, and clinical severity. Furthermore, this study aims to evaluate the epidemiological and clinical ramifications of the emerging variants, including rates of reinfection and breakthrough infections, symptom severity and duration, ICU admission rates, as well as age and comorbidity-adjusted case fatality rates. Additionally, a model will be developed that incorporates variant prevalence over time, vaccination and booster coverage, hospital resource utilization, and mortality rates stratified by variant and demographic characteristics. The model will be validated utilizing historical and current data spanning from 2022 to 2025, alongside simulating forward-looking scenarios extending through 2027. This validation process will encompass stress-testing the model against hypothetical variant surges, shifts in vaccine efficacy, and alterations in public health policies. The intent is to furnish actionable insights for health policymakers by estimating future healthcare demand under various variant prevalence scenarios. By accomplishing these objectives, this research aspires to bridge the existing gap between genomic surveillance and operational health forecasting. In contrast to conventional models that regard COVID-19 evolution as exogenous, this study explicitly acknowledges the endogenous nature of variant development and its integration within local transmission contexts. Consequently, the proposed modeling approach seeks to furnish a more realistic and nuanced perspective on the future trajectory of COVID-19 and its implications for healthcare systems.

4. RESEARCH METHODOLOGY

4.1 Data Source

The dataset's extensive records facilitate comparisons of pandemic responses between countries, aiding in the evaluation of different non-pharmaceutical interventions' effectiveness. The dataset's detailed metrics enable researchers to assess the effectiveness of various public health interventions and track the evolution of the pandemic over time. The data used is from the **Our World in Data** COVID-19 dataset consist of 429435 Rows and 67 columns. This dataset includes comprehensive information on testing, cases, and governmental responses across multiple countries, enhancing the understanding of the pandemic's impact. Here's a **detailed description of the dataset features**, grouped by categories such as location (Country name), date(Daily records), new_deaths_per_million, hosp_patients_per_million, positive_rate. The United States, Canada, Italy, and India were chosen for their varied pandemic patterns, healthcare systems, and diverse geographic representation.

4.2 Identifiers & Metadata

The identifiers and metadata derived from the COVID-19 dataset, as presented in Table Numbers 2 to 5, refer to the essential data attributes and descriptive information extracted to facilitate analysis, interpretation, and data organization. The metadata encompasses contextual details like date of diagnosis, geographical location, testing method, demographic information, and case status.

4.2.1 Dataset features

Table 1. Data set features

Feature	Description
iso_code	3-letter country code (ISO 3166-1 alpha-3)
Continent	Continent where the country is located
Location	Country or region name
Date	Observation date (YYYY-MM-DD)
Population	Total population of the country
population_density	People per square kilometre
median_age	Median age of the population
aged_65_older	% of population aged 65 and older
aged_70_older	% of population aged 70 and older
gdp_per_capita	GDP per capita (USD, PPP-adjusted)
extreme_poverty	% of population in extreme poverty
human_development_index	Composite measure of development (0–1)
Location	Country/region name (e.g., India, Italy)

4.2.2 Epidemiological Data

Table 2. Epidemic data

Feature	Description
total_cases	Cumulative confirmed cases
new_cases	New daily confirmed cases
new_cases_smoothed	7-day rolling average of new cases
total_cases_per_million	Normalized cumulative cases per million
new_cases_per_million	Normalized new cases per million
total_deaths	Cumulative confirmed deaths
new_deaths	Daily new deaths
new_deaths_smoothed	7-day rolling average deaths
total_deaths_per_million	Cumulative deaths per million
new_deaths_per_million	Daily new deaths per million
reproduction_rate	Estimated R-value (spread rate)

4.2.3 Vaccination Data

Table 3. Vaccination data

Feature	Description
total_vaccinations	Total vaccine doses administered
people_vaccinated	Individuals with at least one dose
people_fully_vaccinated	Individuals with a full vaccination schedule
new_vaccinations	New vaccine doses administered
total_boosters	Total booster doses given
new_vaccinations_smoothed	7-day rolling average of new vaccinations
total_vaccinations_per_hundred	Vaccinations per 100 people
people_vaccinated_per_hundred	% of population with at least one dose
people_fully_vaccinated_per_hundred	% fully vaccinated
total_boosters_per_hundred	Booster doses per 100 people

4.2.4 Other Metrics

Table 3. Supplementary metrics

Feature	Description
cardiovasc_death_rate	Cardiovascular death rate (pre-pandemic)
diabetes_prevalence	Diabetes prevalence in %
female_smokers	% of female smokers
male_smokers	% of male smokers
handwashing_facilities	% with basic handwashing access
hospital_beds_per_thousand	Health infrastructure
life_expectancy	Average life expectancy
excess_mortality	% of deaths above expected value

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4.3 Modeling Tools, Metrics, and Scope

This study employs the Facebook Prophet model—an additive regression framework with support for trend shifts, seasonality, and holiday effects—to forecast key COVID-19 health indicators. The analysis focuses on three primary metrics: Daily New Deaths per Million, Hospital Patients per Million, and the COVID-19 Test Positivity Rate. Historical data spanning from January 2020 to June 2024 was used, with projections extending through December 2027. The data was processed at a daily frequency and smoothed using a 7-day rolling average for clarity. The study covers four countries with varied pandemic dynamics and health infrastructures: the United States, Canada, Italy, and India. Key Python libraries used include Prophet, pandas, matplotlib, and seaborn.4.6 Prophet Model Basics

4.4 Prophet Model:

Prophet is an open-source time series forecasting tool created by Meta (formerly Facebook) for modeling data with seasonality, holidays, missing values, and non-linear trends. Originally designed for business applications like sales and traffic, it has proven effective in epidemiological forecasting, including COVID-19 trends. It uses an additive regression model by default, with optional multiplicative seasonality. Prophet is known for being fast, interpretable, and robust to outliers.

COMPONENT	MATHEMATICAL FORMULA	PARAMETERS	EXPLANATION
Prophet Model Structure	$y(t) = g(t) + s(t) + h(t) + \varepsilon t$	y(t): observed value, g(t): trend(Linear and Logistic), s(t): seasonality, h(t): holiday effect, εt: error	Decomposes time series into trend, seasonality, holiday, and noise components
Trend (Linear)	$g(t) = (k + a(t)^{T}\delta)(t - t_0) + (m + a(t)^{T}\gamma)$	k: initial growth rate, a(t): change-point indicators, δ: rate changes, m: offset, γ: offset shifts	Models non-linear trends by adjusting slope and offset at detected change-points
Trend (Logistic)	$g(t) = \frac{C}{1 + \exp(-k(t - m))}$	C: carrying capacity, k: growth rate, m: inflection time	Used when growth saturates (e.g., vaccinated population or ICU bed limits)
Seasonality	$s(t) = \sum_{\{n=1\}}^{N} [a_n\cos(\{2\pi nt/P\}) + b_n\sin(\{2\pi nt/P\})]$	P: period, N: number of terms, a_n, b_n: Fourier coefficients	Captures cyclic behaviour using a Fourier series (supports multiple seasonal patterns)
Holiday Effects	$h(t) = \sum_{i} \kappa_i D_{i(t)}$	$D_i(t)$: binary indicator if day t is holiday i, κ_i: strength of holiday effect	Allows modelling of short-term impact due to known events (e.g., lockdowns, festivals)
Error Term	$\varepsilon t \sim N(0,\sigma 2)$	σ2: variance of noise	Represents the unexplained variation or residuals in the data
Change-Points	Automatically detected or user-defined	affects δ, γ in linear trend	Locations in time where the trend significantly changes direction or rate

5. RESULTS AND VISUALIZATION

The results and visualizations of the research findings are organized into three key sub-domains to provide a comprehensive understanding of COVID-19 trends. These sub-domains include: Daily New Deaths per Million**,** which highlights mortality patterns and their temporal shifts across countries; Hospital Patients Forecast, offering insights into projected healthcare burden during various seasons; and COVID-19 Test Positivity Rate Forecast, which reflects community transmission intensity and testing adequacy. Together, these categories enable a nuanced interpretation of the pandemic's trajectory, helping inform public health responses, policy planning, and preparedness for future surges or variant-driven outbreaks.

5.1 Daily New Deaths per Million

The projected trends of daily new COVID-19 deaths per million in the United States, Canada, Italy, and India (Figures 1–4) demonstrate a clear decline from the pandemic's early peaks in 2020–2021, particularly in Italy and the U.S., which experienced the highest fatality rates. Canada and India showed smaller but significant surges. From 2022 onward, the death rates gradually flatten, likely due to widespread vaccination, improved healthcare responses, and natural immunity.

Prophet model forecasts through 2027 suggest a continued low-level trend with only minor seasonal upticks—especially during winters—possibly linked to waning immunity and indoor transmission. While the virus appears to have become endemic, no major resurgence in mortality is anticipated.

In comparison:

- **Italy** shows the sharpest early spikes but declines steadily.
- **The U.S.** displays moderate recurring peaks, leveling off post-2023.
- **Canada** follows a more stable, less volatile path.
- **India** reflects a flatter trend with less variability in recent years.

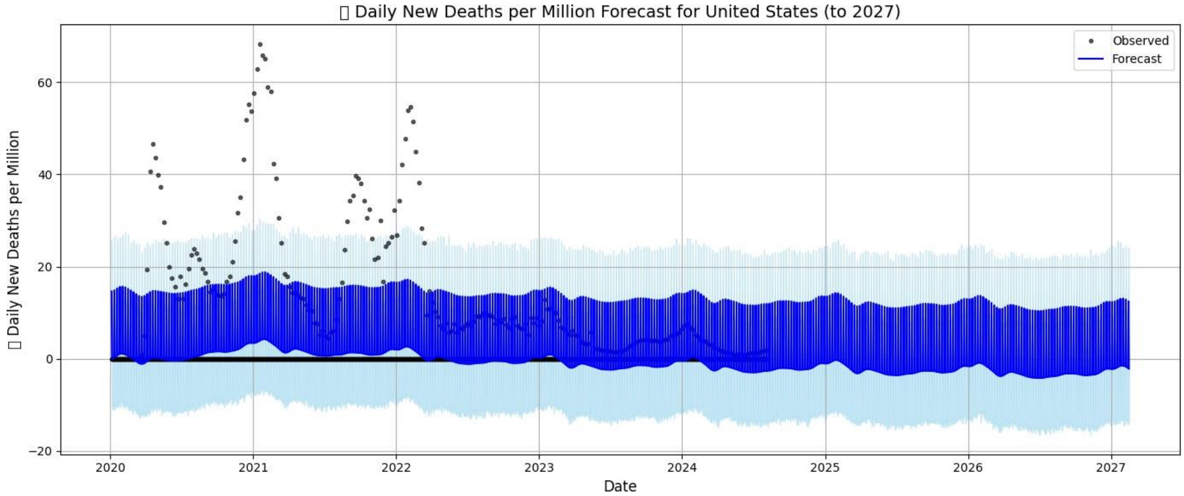

Figure.1 Forecast of New Deaths per Million-US

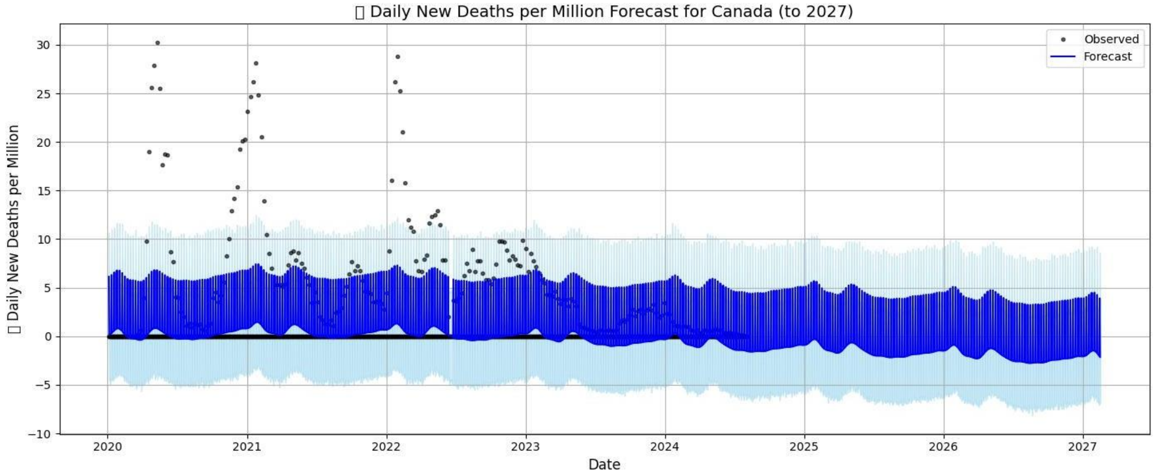

Figure.2 Forecast of New Deaths per Million-Canada

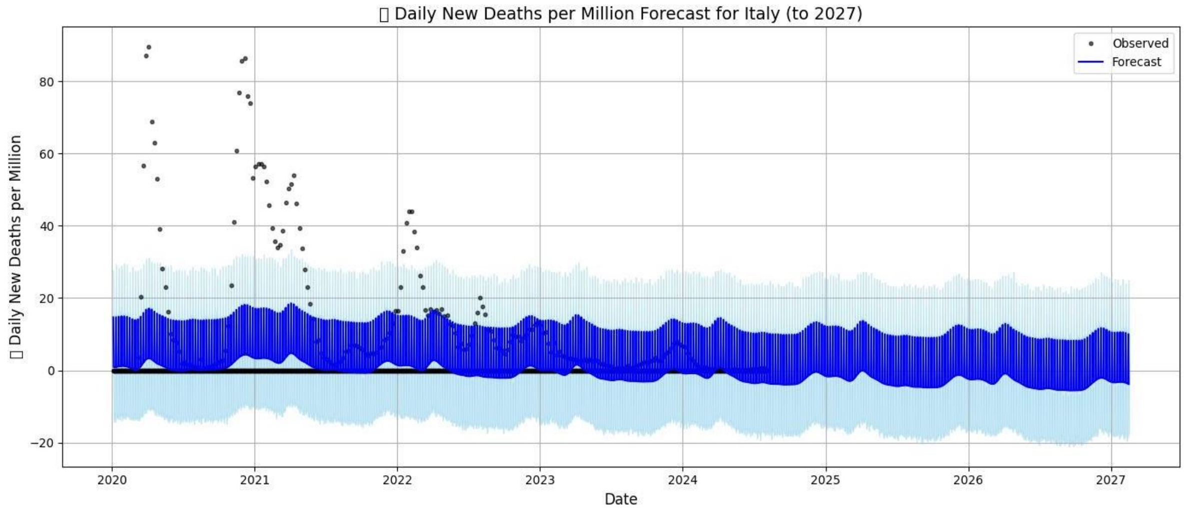

Figure.3 Forecast of New Deaths per Million-Italy

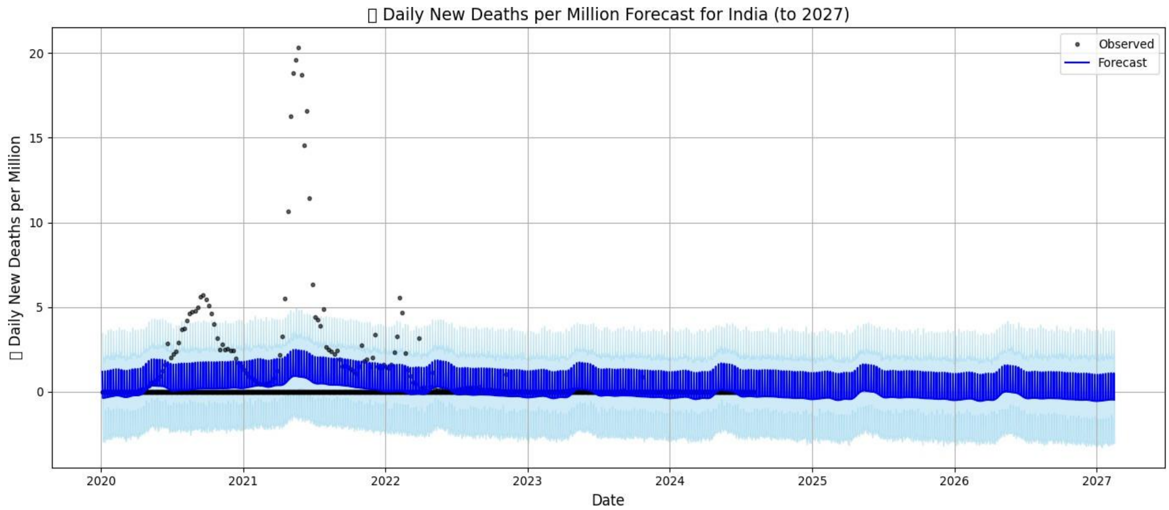

Figure.4 Forecast of New Deaths per Million-India

5.2 Hospital Patients per Million

Figures (5-7) show projected hospitalizations per million in the USA, Canada, Italy, and India through 2027. All countries saw major peaks during 2020–2022, followed by a steady decline, reflecting improved healthcare and vaccination efforts.

The U.S. is expected to experience seasonal spikes, especially in winter, due to combined flu and COVID-19 impact. Canada shows consistently low and stable hospitalizations, aided by strong public health measures and vaccine coverage. Italy mirrors the U.S. in seasonal trends but with lower peaks, though its aging population remains a concern. India displays irregular patterns due to uneven healthcare access and data reporting, leading to more unpredictable trends.

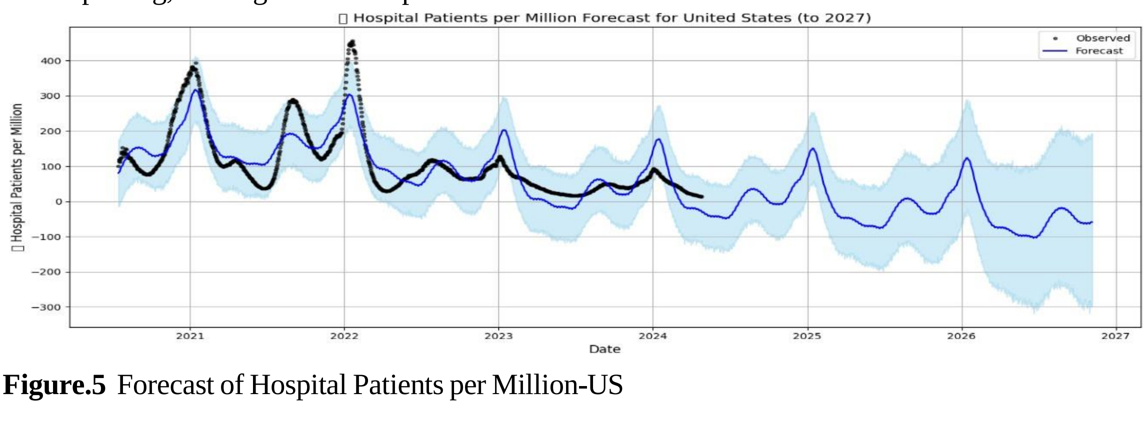

Figure.5 Forecast of Hospital Patients per Million-US

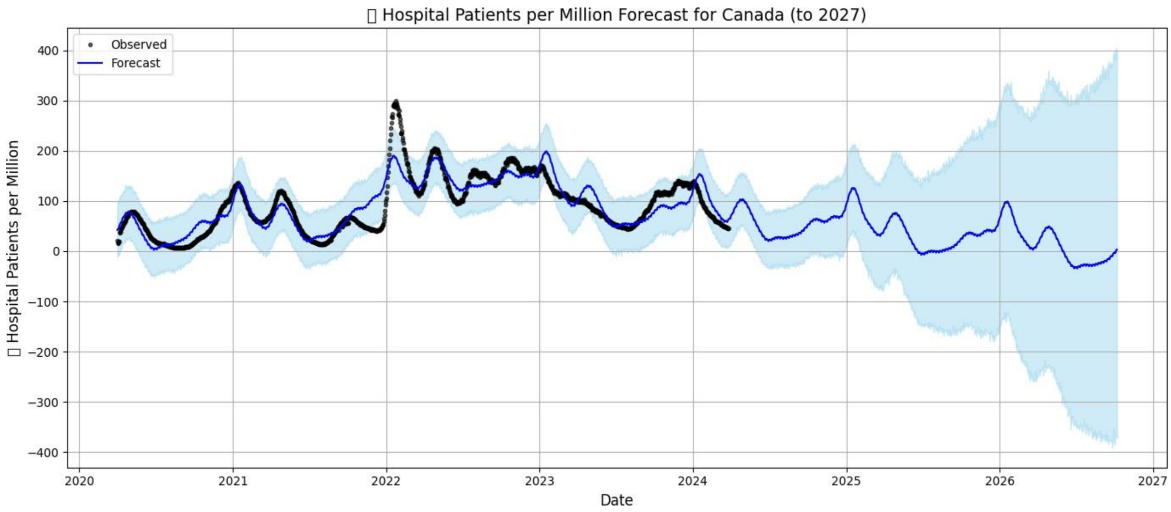

Figure.6 Forecast of Hospital Patients per Million-Canada

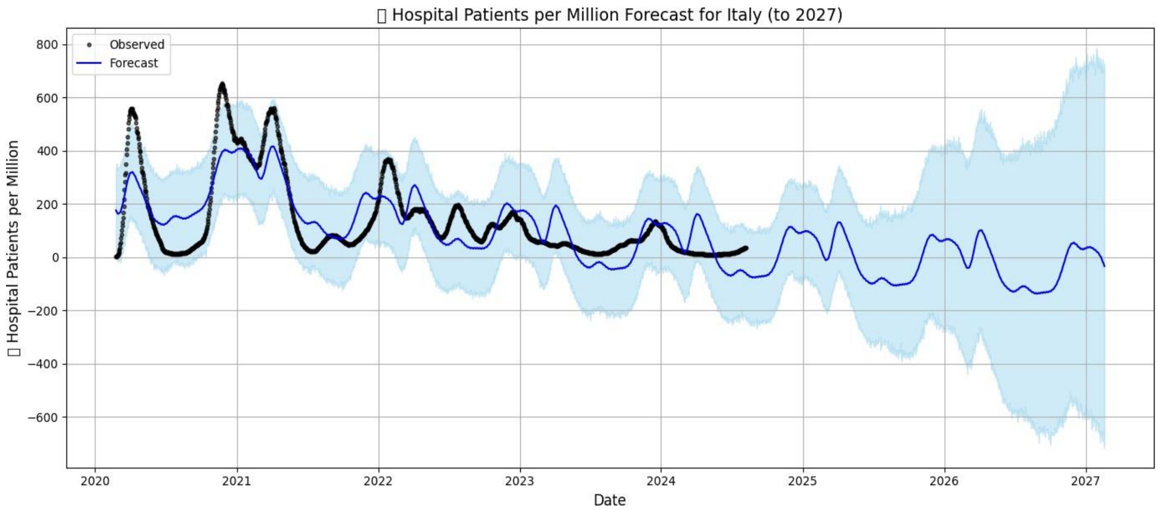

Figure.7 Forecast of Hospital Patients per Million-Italy

Test Positivity Rate

The Figures (8-11) depict forecasted test positivity rates per million for the US, Canada, Italy, and India through 2027. All countries saw sharp peaks during 2020–2022, reflecting major COVID-19 waves. The **US** and **Canada** show a gradual rise with seasonal variations, though Canada's trend remains more stable. **Italy** shows a steep upward trajectory with wide uncertainty, indicating potential data instability. In contrast, **India** displays a steady decline post-2022, suggesting improved outbreak control or reduced testing. Overall, Western nations may face rising positivity rates, while India's outlook appears more stable and declining.

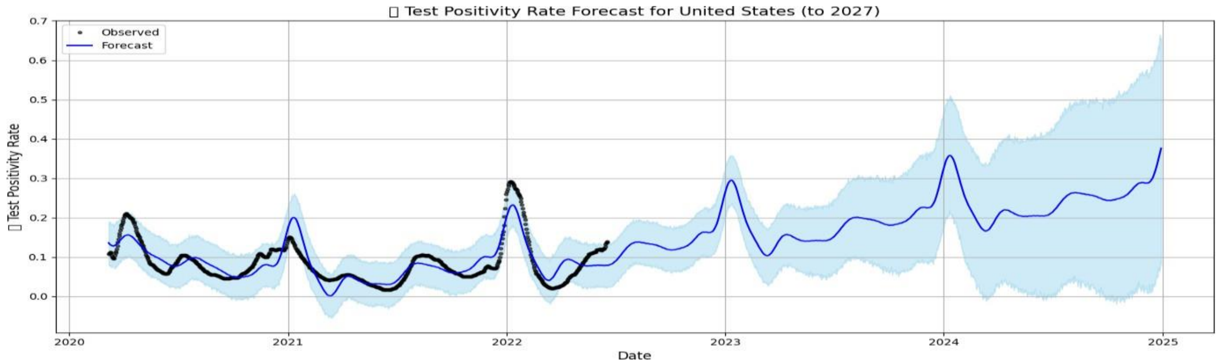

Figure.8 Forecast of Test Positivity Rate

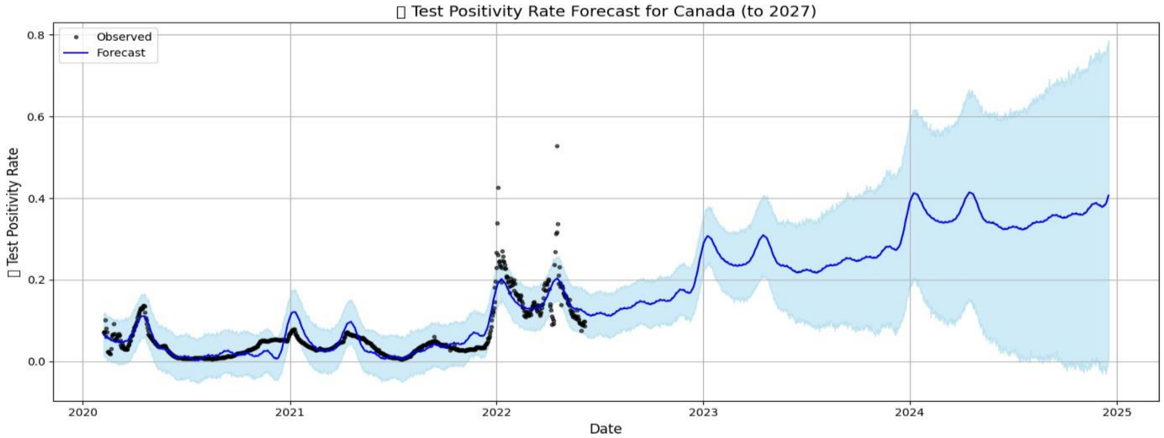

Figure.9 Forecast of Test Positivity Rate-Canada

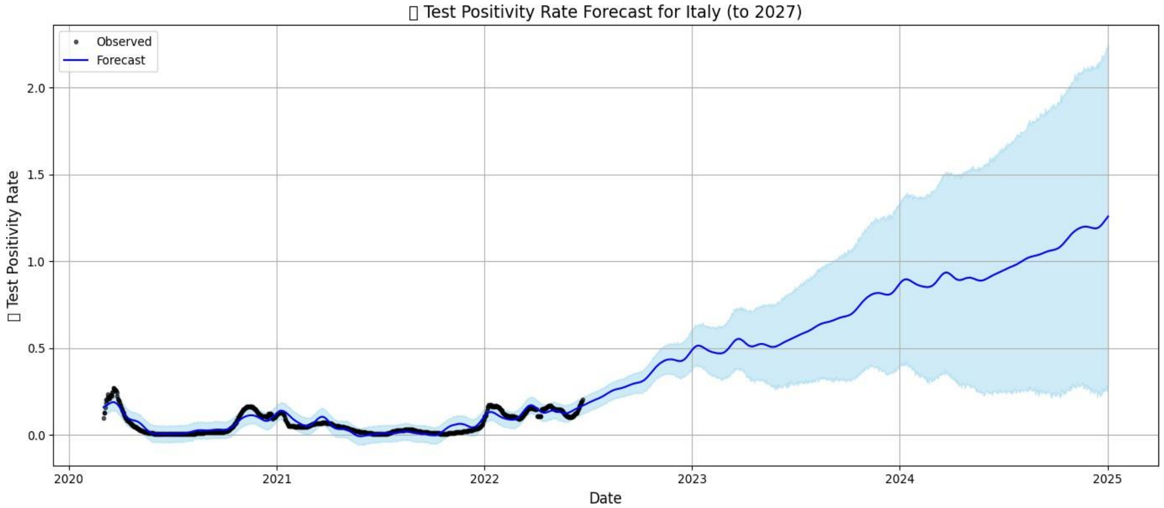

Figure.10 Forecast of Test Positivity Rate-Italy

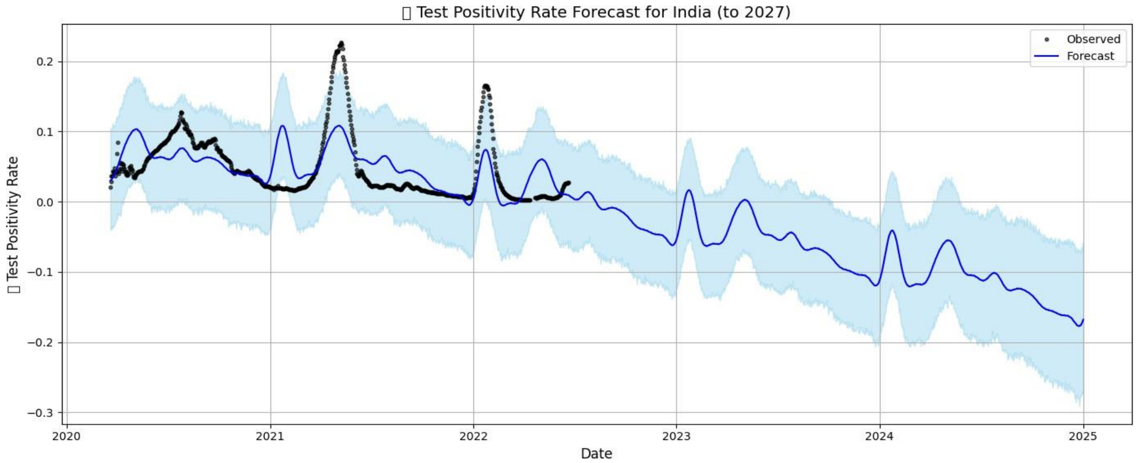

Figure.11 Forecast of Test Positivity Rate-India

6. RESULT ANALYSIS AND DISCUSSIONS

As per finding from results, the table 6 shows, Canada has the most favorable long-term forecast, with consistently low death rates and strong public health management. The USA, while improving, shows greater volatility, possibly due to state-level variations, vaccination hesitancy, and higher comorbidity prevalence. Italy, despite its severe early experience, shows a stabilizing trend, reflecting successful adaptation over time and good seasonal preparedness. All three countries show declining mortality, which is a positive indicator of pandemic control, vaccine effectiveness, and improved treatment protocols.

6.1. Comparative Summary Table

Table 6. Comparative Table

Factor	USA	Canada	Italy
Initial Impact	High	Moderate	Very High (First in Europe)
Peak Deaths/Day per Million	~11	~6	~12
Response Effectiveness	Mixed	Consistent and strong	Strong after early impact
2023–2027 Forecast Level	Low to Moderate	Very Low	Low
Seasonality in Forecast	Present	Minimal	Noticeable
Model Uncertainty	Moderate to High	Low	Moderate
Public Health Resilience	Variable across states	High	Improved over time

Countries with higher transparency and healthcare capacity (like USA, Canada, Italy) show more predictable seasonal cycles. India's flat trends may reflect reporting issues or successful containment

Table 7. Overall metrics comparison

Metric	USA	Italy	Canada	India
Deaths	Stable with seasonal spikes	Moderate seasonal	Mild peaks	Flat
Hospitalizations	High baseline	Moderate cyclical	Mild periodic	Flat/stable
Positivity Rate	Slight rise forecast	Mild increase	Mild rise	Stable/Low

The United States faces seasonal spikes across metrics but trends are stabilizing.

- **Canada** shows the most controlled and consistent forecasts across all metrics.
- **Italy** demonstrates declining deaths but rising test positivity, needing cautious monitoring.
- **India** reflects declining positivity and uncertain hospitalization trends, influenced by regional disparities.

These forecasts suggest that while major pandemic impacts have subsided, ongoing surveillance and preparedness remain essential, especially in regions with high uncertainty or inconsistent data trends.

7. Conclusion and future work

This paper provides a long-term view of COVID-19's likely health impact through 2027. Seasonal patterns, waning immunity, and variant evolution all point toward periodic burdens, especially in deaths and hospitalizations. Proactive planning, surveillance, and adaptive policies are essential for managing the endemic future of COVID-19. Our research study shows that country-specific forecasting provides nuanced views of potential healthcare stress due to COVID-19. While developed countries like the USA and Italy show clearer seasonal patterns, developing nations like India face more erratic but potentially dangerous spikes. These forecasts highlight the need for localized and timely interventions through 2027. We recommend following measures, which helps to decline the vulnerability of covid-19. First, Continue efforts especially for vulnerable and elderly groups, Keep surge capacity in hospitals ready, especially toward 2026–2027, Expand genomic sequencing and rapid testing to detect emerging variants, Maintain public communication around seasonal infection peaks and finally we need regular updates with real-time data to adjust strategies. Moreover, we are recommending to continuity of the research work to follow vaccination status, mobility, and variant-specific datasets. The availability of updated new data and real-time model to be concentrated and extension to regional-level predictions within each country is also mandatory to improve the strategy.

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