JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

TIME SERIES FORECASTING MODEL: A REVIEW STUDY

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Abstract:
Time series forecasting utilizes data collected at regular intervals to capture trends, seasonality, and other patterns, enabling reliable prediction of future values. This study elaborates on the analytical views of different researchers using different time series models. In the context of pandemics, such forecasting supports public health by predicting case counts, hospitalizations, and deaths, thereby guiding interventions, resource allocation, and communication strategies. The COVID-19 pandemic, caused by SARS-CoV-2, has emerged as the twenty-first century's most significant public health crisis. The pandemic underscored the importance of robust forecasting models in healthcare planning and policymaking. Among forecasting approaches, time-series models, including ARIMA, SARIMA, Prophet, and hybrid extensions, have been widely employed to predict daily and cumulative cases, deaths, and recovery trends. Evidence suggests ARIMA-based models demonstrate high reliability for short-term forecasting when data is limited or unstable. This paper aims to discuss forecasting techniques, review existing approaches, and emphasize the need for adaptive, interpretable, and data-driven forecasting models to enhance preparedness and resilience in responding to future pandemic-like situations.

Key Words: Time Series, Forecasting, Analysis, ARIMA, Hybrid Models, Public Health, COVID-19, Pandemic Prediction.

1. Introduction

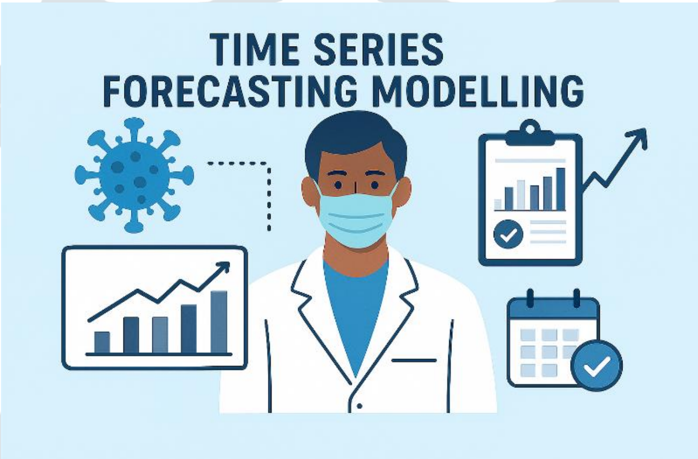
Health is universally recognized as the foundation of societal well-being and economic growth. According to the World Health Organization (WHO), Health is a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity. [15] When health crises escalate into pandemics, they disrupt societies, overwhelm healthcare systems, and challenge economic stability. In such circumstances, forecasting becomes a crucial tool for preparedness and resilience.

Forecasting serves as an essential scientific approach for anticipating future events through the analysis of historical and current data patterns. It provides early insights into potential developments and guides timely decision-making in diverse domains, including economics, climate science, energy, and healthcare. Among many approaches to forecasting, time series modelling has gained prominence due to its ability to capture temporal dynamics and transform historical data into actionable predictions. A time series represents sequential observations collected at regular intervals, and its analysis reveals meaningful patterns such as long-term trends, seasonality, and cyclical variations. Models such as the Autoregressive Integrated Moving Average (ARIMA) and its seasonal counterpart SARIMA have been widely adopted because of their simplicity, interpretability, and strong performance in short-term forecasting. In recent years, advanced techniques such as exponential smoothing, Prophet, and hybrid approaches that integrate statistical models with machine learning and deep learning methods, including ARIMA-LSTM, have further enhanced forecasting accuracy, especially in complex, nonlinear, or long-term scenarios. These tools have proven indispensable in public health, where accurate predictions can save lives by informing preparedness and intervention strategies.

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, represents one of the most critical global health crises of the twenty-first century. First detected in Wuhan, China, in December 2019, the virus rapidly spread across the globe, leading the World Health Organization to declare it a pandemic on March 11, 2020. India reported its first case in Kerala on January 30, 2020, and soon experienced multiple waves of infection that profoundly strained the healthcare system. The first wave peaked in September 2020 with nearly 97,000 daily cases, followed by a catastrophic second wave in April–May 2021, intensified by the Delta variant, during which daily cases surpassed 400,000 and oxygen shortages overwhelmed hospitals. In early 2022, the Omicron variant precipitated a third wave, which spread quickly but caused milder disease due to widespread vaccination and prior exposure. By mid-2022, India had administered more than 2 billion vaccine doses, significantly enhancing population-level immunity. From 2023 onward, COVID-19 largely transitioned into an endemic phase, though periodic surges linked to Omicron sub-variants such as XBB.1.5 and EG.5 continued. In early 2025, newer sub-variants briefly increased case counts but were managed effectively through vaccination, surveillance, and rapid interventions. This historical trajectory illustrates not only the evolving nature of the pandemic but also the urgent need for predictive tools to anticipate case surges, mitigate their impact, and guide public health responses.

The COVID-19 crisis has generated a vast body of research on epidemic prediction, particularly using time series models. This interest arises from the fact that the pandemic unfolded in successive waves, often driven by unpredictable variants, with profound implications for healthcare infrastructure, vaccination strategies, and policy decisions. In India, where reliable and structured COVID-19 data became available through national platforms, time series models such as ARIMA demonstrated strong potential for short-term forecasting, supporting resource allocation and intervention planning. At the same time, hybrid and deep learning models have been increasingly employed to capture complex, nonlinear patterns and long-term fluctuations. However, challenges remain, including data quality limitations, uncertainty in variant evolution, and regional differences in model applicability.

This review aims to synthesize existing literature on the application of time series modelling in forecasting COVID-19, highlighting key contributions while examining the comparative strengths and limitations of different forecasting models. By situating COVID-19 within the broader field of time series forecasting, the review seeks to provide insights for improving predictive accuracy, supporting healthcare preparedness, and enhancing resilience against future public health emergencies.



2. Research Methodology

Research Design:

The present study adopts a systematic review design to synthesize existing research related to COVID-19 forecasting with a specific emphasis on time series modelling. Literature published between 2020 and 2025 was considered, as this period captures the critical phases of the pandemic and the eventual transition toward an endemic stage. The review mainly concentrates on evidence-based studies that utilized time series methods to project confirmed cases, deaths, or recoveries, thereby offering evidence on the strengths and weaknesses of these models. Within the scope of this study, COVID-19 forecasting is defined as the use of historical epidemiological data to model and predict future patterns of the pandemic with the help of different statistical and hybrid time series techniques. The goal of this study is to assess how different models performed in different contexts, highlight their contributions, and examine how forecasting approaches evolved throughout the pandemic years.

Selection Criteria and Sources of Data:

Relevant studies were identified through structured searches of major academic databases, such as Scopus, Web of Science, PubMed, and Google Scholar. The search covered the period from 2020 to 2025, ensuring that the research captured both the early outbreak period and the more recent endemic phase of COVID-19. The following keywords were used: “COVID-19 forecasting,” “time series analysis,” “ARIMA,” “SARIMA,” “Prophet,” “exponential smoothing,” “hybrid forecasting models,” and “pandemic prediction.” Reference lists of selected articles were also checked to capture additional relevant works. The review concentrated on studies employing models such as ARIMA, SARIMA, Prophet, Exponential Smoothing, and hybrid approaches combining statistical and machine learning methods to forecast short-term and long-term pandemic trends. This structured strategy ensured the inclusion of a wide-ranging and balanced review of forecasting methods applied in the COVID-19 context.

3. Review of Literature

The coronavirus crisis has spurred extensive research on forecasting its spread, with time series modeling emerging as a key approach for understanding and predicting case counts, hospitalizations, and fatalities. By analyzing historical data and capturing trends and seasonality, models such as ARIMA, SARIMA, Prophet, exponential smoothing, and hybrid techniques integrating machine learning and deep learning have been widely applied. This review synthesizes existing studies, assessing the methodological contributions, comparative accuracy, and practical relevance of these forecasting approaches in guiding public health planning and pandemic responses.

Yadav et al. (2025) analyzed the geospatial spread of COVID-19 across Indian states and Union Territories during the Alpha, Delta, and Omicron waves. Using data from the COVID-19 India API, they applied ARIMA alongside machine learning models such as Decision Tree and SVR. Evaluation with RMSE, MAE, MAPE, AIC, and BIC indicated that ARIMA consistently outperformed the machine learning models, producing lower forecast errors.

Jain et al. (2024) introduced a novel ensemble framework integrating ARIMA with LSTM to strengthen global outbreak preparedness. They evaluated ARIMA, LSTM, Prophet, ARIMA–LSTM, and ARIMA–ANN for global COVID-19 prediction, including India, the USA, Brazil, and Russia, using Johns Hopkins University data. Their evaluation using MAPE, SMAPE, and MDAPE showed that the ARIMA–LSTM hybrid consistently achieved the highest accuracy across countries, demonstrating the robustness of hybrid approaches for large-scale forecasting and policy guidance.

Kanmani et al. (2024) conducted a comparative study on forecasting COVID-19 cases in India using ARIMA, Artificial Neural Networks (ANN), and Exponential Smoothing. Using data from the PRS India database, model performance was assessed through RMSE values. Their findings revealed that ANN provided the most accurate predictions, while ARIMA and Exponential Smoothing models recorded moderate errors. Their findings emphasized ANN's superiority for complex pandemic dynamics.

Rajendar et al. (2024) conducted a study on forecasting COVID-19 cases in India using ARIMA, LSTM, and Bi-LSTM models. Utilizing the WHO COVID-19 database, the models were evaluated based on RMSE values. The findings revealed that LSTM consistently achieved the lowest error rates, outperforming ARIMA. The study highlighted the effectiveness of deep learning models, particularly LSTM, in providing more accurate and reliable pandemic predictions.

Bahuguna et al. (2023) carried out a comparative analysis of ARIMA (0,0,2) and Holt-Winters exponential smoothing to forecast COVID-19 cases in Uttarakhand. Using confirmed case data from the MoHFW Uttarakhand database, the models were evaluated through RMSE and MAE. The results indicated that ARIMA (0,0,2) performed better for short-term forecasting, while exponential smoothing was more effective for long-term predictions. This study emphasized the complementary strengths of statistical models in pandemic forecasting.

Sardar et al. (2023) aimed to evaluate the effectiveness of machine learning and traditional time series models in forecasting COVID-19 cases across SAARC countries. Using data from GitHub Repository and Our World in Data, they compared ARIMA, Prophet, GLMNet, XGBoost, and Random Forest models, with performance measured through RMSE, MAE, and MAPE. Their findings revealed that ARIMA consistently outperformed the machine learning and Prophet models in predicting confirmed cases, highlighting its reliability for short-term forecasts in the SAARC region.

Jin et al. (2022) proposed a hybrid forecasting approach integrating ARIMA with LSTM to predict COVID-19 trends in India and China. Using the Johns Hopkins University dataset, the study compared ARIMA, LSTM, ARIMA–LSTM hybrid, and SVR models, evaluated through MAPE, RMSE, MAE, MSE, and R^2 metrics. The results demonstrated that the ARIMA–LSTM hybrid consistently outperformed standalone ARIMA and SVR, underscoring the robustness of hybrid models in improving pandemic prediction accuracy.

Tandon et al. (2022) applied the ARIMA model to forecast short-term COVID-19 cases in India using the Johns Hopkins University dataset. Model accuracy was assessed through MAPE, MAD, and MSD values. The study found that ARIMA effectively predicted a rising trend in near-future cases, underscoring its utility for short-term pandemic forecasting.

Wang et al. (2022) compared ARIMA, SARIMA, and Facebook Prophet models to forecast daily and cumulative COVID-19 cases in India, the USA, and Brazil using data from the WHO COVID-19 dashboard. Model performance was evaluated using RMSE, MAE, and MAPE. Results indicated that ARIMA provided the most accurate short-term forecasts for India, while Prophet performed better in the USA.

Mangla et al. (2021) conducted short-term COVID-19 forecasting in India and the five most affected states using Exponential, Logistic, Gompertz, and ARIMA models with data from the COVID-19 India API website. Model performance was evaluated using AIC, MAPE, and RMSE. Findings revealed that ARIMA provided the best-fit model for COVID-19 case trends across India and the selected states.

Wang et al. (2021) conducted a comparative study of COVID-19 forecasting for the second wave in India and the USA using ARIMA, Exponential Smoothing (ES), Generalized Regression Neural Network (GRNN), and a hybrid ARIMA–GRNN model, based on data from WHO and Our World in Data. Model performance was assessed using MAPE, revealing that ARIMA provided the most accurate predictions for India, while the hybrid ARIMA–GRNN model outperformed others in the USA.

Kumar & Susan (2020) analyzed COVID-19 pandemic prediction using ARIMA and Facebook Prophet models across the top 10 affected countries, including India, based on data from GitHub Repository. Evaluation metrics included MAE, RMSE, and MAPE, with results showing that ARIMA outperformed Prophet for India's short-term forecasts, clearly highlighting its effectiveness in capturing pandemic trends and supporting timely public health interventions.

Richa and Saini (2025) reviewed various time series models for air quality forecasting, noting that ARIMA and SARIMA are effective for short-term predictions, while hybrid and deep learning models like LSTM capture complex patterns with greater accuracy. In a related study, they applied the Link Relative Method to AQI data, revealing severe pollution during winter and marked improvement during monsoon months. These findings suggest that ARIMA serves as a reliable baseline, but integrating hybrid approaches with seasonal analysis can enhance forecasting accuracy and support better environmental and public health policies.

The analysis of existing literature underscores evolving trends in COVID-19 time series forecasting. Classical statistical models like ARIMA and SARIMA continue to perform well for short-term predictions. In contrast, hybrid approaches that integrate statistical, machine learning, and deep learning techniques demonstrate enhanced accuracy for extended forecasts. Hybrid and deep learning models, such as LSTM and ARIMA–LSTM hybrids, effectively capture nonlinear trends and complex outbreak dynamics over longer horizons. Despite significant advancements, challenges, including inconsistent data, underreporting, regional disparities, and computational demands, still limit model reliability. Future studies should aim to refine hybrid frameworks, incorporate real-time datasets, and adopt innovative machine learning and deep learning strategies to deliver more robust, accurate, and actionable pandemic predictions, ultimately strengthening public health preparedness and response.

Table 1: Summary Table of Literature Reviewed

Author(s) & Year	Models Used	Study Region	Data Source & Range	Evaluation Metrics	Key Findings
Yadav et al. (2025)	ARIMA, machine learning models	All Indian states & UTs, India	COVID-19-India API websites (Jan 31, 2020–Jan 30, 2022)	RMSE, MAE, MAPE, AIC, BIC	ARIMA outperformed Decision Tree and SVR with lower RMSE
Jain et al. (2024)	ARIMA, LSTM, GRU, Prophet, ARIMA-LSTM, ARIMA-ANN	Global (including India, USA, Brazil, Russia)	Johns Hopkins University COVID-19 dataset (Jan 22, 2020 - Mar 9, 2023)	MAPE, SMAPE, MDAPE	Hybrid ARIMA–LSTM achieved the highest accuracy across countries, outperforming standalone ARIMA
Kanmani et al. (2024)	ARIMA, ANN, Exponential Smoothing	India	PRS India database (Jan–Dec, 2021)	RMSE	ANN achieved the best accuracy; ARIMA & Exponential showed moderate errors
Rajendar et al. (2024)	ARIMA, LSTM, Bi-LSTM	India	WHO COVID-19 database (Mar 2022–Jul 2023)	RMSE	LSTM consistently produced the lowest RMSE, outperforming ARIMA
Bahuguna et al. (2023)	ARIMA (0,0,2), Exponential smoothing (Holt-Winters)	Uttarakhand (India)	MoHFW Uttarakhand confirmed cases (Jan 2021 – Dec 2022)	RMSE, MAE	ARIMA (0,0,2) is best for short-term; exponential smoothing suits long-term
Sardar et al. (2023)	ARIMA, Prophet, GLMNet, XGBoost, Random Forest ML Model	SAARC countries (including India)	GitHub Repository & Our World in Data (Jan 31 – Jul 19, 2020)	RMSE, MAE, MAPE	ARIMA outperforms others in forecasting confirmed cases in SAARC nations
Jin et al. (2022)	ARIMA, LSTM, ARIMA-LSTM Hybrid, SVR	India, China	Johns Hopkins University COVID-19 dataset (Jan 1, 2021 - Oct 10, 2022)	MAPE, RMSE, MAE, MSE, R^2	ARIMA-LSTM hybrid model outperformed ARIMA & SVR models
Tandon et al. (2022)	ARIMA	India	Johns Hopkins University COVID-19 dataset (Jan 22 – Apr 13, 2020)	MAPE, MAD, MSD	ARIMA predicted increasing short-term COVID-19 cases
Wang et al. (2022)	ARIMA, SARIMA, Facebook Prophet Model	India, USA, and Brazil,	WHO COVID-19 dashboard (May 1, 2020 – Nov 30, 2021)	RMSE, MAE, MAPE	ARIMA performed best in India’s short-term forecasts; Prophet excelled in the USA
Mangla et al. (2021)	Exponential, logistic, Gompertz, ARIMA	India and the five most affected states	COVID-19-India API website (Jan 30 – Dec 20, 2020)	AIC, MAPE, RMSE	ARIMA provided the best-fit model for COVID-19 case trends in India and the states
Wang et al. (2021)	ARIMA, ES, GRNN, ARIMA–GRNN hybrid	India, USA	WHO & Our World in Data (Mar 1, 2020 – May 27, 2021)	MAPE	ARIMA performed best in India; the hybrid model outperformed in the USA
Kumar & Susan (2020)	ARIMA, Facebook Prophet Model	Global (Top 10 countries, including India)	GitHub Repository (Jan 22 – May 20, 2020)	MAE, RMSE, MAPE	ARIMA outperformed Prophet for India’s short-term COVID forecasts

4. Research Gap

Even with substantial progress in deploying time series techniques for pandemic prediction, several critical gaps persist. A large proportion of studies have relied on classical approaches such as ARIMA and SARIMA, which perform well for short-term predictions but often struggle to capture the nonlinear and rapidly changing dynamics of pandemic data. Advanced models like LSTM, Bi-LSTM, and hybrid ARIMA–LSTM frameworks have shown promising accuracy; however, their high computational cost, dependence on large datasets, and limited interpretability restrict their broader application. Another major limitation lies in the quality and consistency of data issues, such as missing values, irregular updates, and region-specific reporting practices, which undermine model robustness. An additional concern is that many studies concentrated on country-level or regional case forecasting, with fewer attempts at developing generalized models adaptable across different geographies and phases of the pandemic. Long-term forecasting, particularly in the context of emerging variants and vaccination effects, also remains underexplored. Addressing these gaps requires the development of adaptive, computationally efficient, and advanced time series models that integrate epidemiological factors and can deliver reliable forecasts across varying temporal and spatial scales.

5. Result

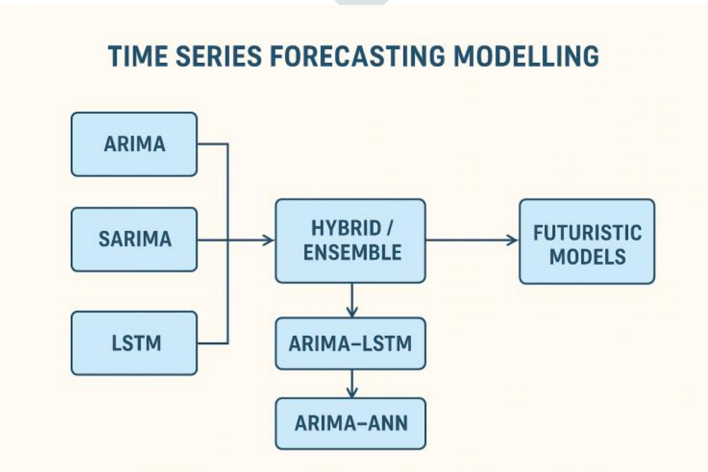
The reviewed literature demonstrates that time series models have played a pivotal role in forecasting COVID-19 cases across different regions. Traditional statistical approaches such as ARIMA, SARIMA, and Prophet proved effective for short-term predictions, particularly during the early phases of the pandemic. However, their limitations in handling nonlinearity and complex patterns became evident over time. Deep learning methods like LSTM, Bi-LSTM, and GRU consistently outperformed statistical models by capturing long-term dependencies and nonlinear dynamics, thereby achieving lower error rates. Hybrid and ensemble approaches, including ARIMA–LSTM and ARIMA–ANN, further enhanced predictive performance by leveraging the strengths of both statistical and machine learning models. Collectively, these studies highlight a clear progression from simple statistical forecasting towards advanced hybrid and deep learning methodologies, with significant improvements in accuracy and robustness.

6. Conclusion

This review underscores the critical role of time series modelling in COVID-19 forecasting, where accurate predictions serve as a cornerstone for informed public health decisions and timely interventions. While traditional statistical approaches such as ARIMA, SARIMA, and Exponential Smoothing have been valuable for short-term case projections, hybrid approaches that combine statistical foundations with machine learning models like Random Forest and XGBoost have shown stronger adaptability by leveraging both temporal dependencies and intricate epidemic patterns. Meanwhile, deep learning architectures such as LSTM, Bi-LSTM, and GRU have demonstrated superior accuracy in capturing non-linearities but remain constrained by high data requirements and computational intensity. The evidence suggests that no single model offers universal superiority; rather, model choice must align with data characteristics, resource availability, and the specific forecasting objective. Looking ahead, future research should emphasize robust hybrid frameworks, advanced preprocessing strategies, and cross-country validations to enhance both the accuracy and the transferability of COVID-19 forecasts. Strengthening these modelling approaches will not only improve pandemic response but also lay the groundwork for managing future global health crises.

7. Futuristic Approach

Future approaches in COVID-19 forecasting should focus on developing more adaptive, intelligent, and interpretable time series models. The integration of deep learning frameworks such as LSTM, GRU, and attention-based architectures with traditional models like ARIMA and Prophet can create powerful hybrid systems capable of capturing both short-term fluctuations and long-term epidemic dynamics. Incorporating real-time data sources—such as mobility patterns, vaccination coverage, social media sentiment, and environmental variables will further enhance prediction reliability. Moreover, explainable AI techniques can be applied to ensure transparency in model outputs, making forecasts more actionable for policymakers. Cloud-based platforms and automated pipelines for continuous model updating will also play a pivotal role in handling dynamic pandemic data. Ultimately, the futuristic direction should emphasize hybridization, real-time adaptability, and cross-domain integration to build resilient forecasting systems that can guide public health strategies not only for COVID-19 but also for future infectious disease outbreaks.



References:

1. **Yadav S.K., Mehra M., Mishra H.R., Akhter Y.**, "Interpreting the COVID-19 infection geospatial data of Indian provinces for Alpha, Delta, and Omicron variants using ARIMA and Machine Learning", *International Journal of Biomathematics*, 2025 Feb 19, https://doi.org/10.1142/S1793524525500135

2. **Jain S., Agrawal S., Mohapatra E., Srinivasan K.**, "A novel ensemble ARIMA–LSTM approach for evaluating COVID-19 cases and future outbreak preparedness", *Health Care Science*, 2024 Aug 11; 3:409–425, https://doi.org/10.1002/hcs2.123

3. **Kanmani G.R., Lakshmi G., Dhivya Devi S., Maheswari P.**, "Forecasting by Time Series Models for COVID-19 Cases in India – A Comparative Study", *Frontiers in Health Informatics*, 2024, 13(3), 8585–8599, https://doi.org/10.63682/fhi255

4. **Rajendar M., Reddy D.M., Nagaraju V.**, "An Accurate Model for COVID-19 Positive Cases in India by using Traditional ARIMA and Artificial Neural Networks (LSTM and Bi-LSTM)", *Indian Journal of Science and Technology*, 2024 June 4, 17(23), 2421–2429, https://doi.org/10.17485/IJST/v17i23.976

5. **Bahuguna A., Uniyal A., Sharma N., Semwal J.**, "Comparison of exponential smoothing and ARIMA time series models for forecasting COVID-19 cases: a secondary data analysis", *International Journal of Research in Medical Sciences*, 2023 May, 11(5), 1727–1734, https://doi.org/10.18203/2320-6012.ijrms20231344

6. **Sardar I., Akbar M.A., Leiva V., Alsanad A., Mishra P.**, "Machine learning and automatic ARIMA/Prophet models-based forecasting of COVID-19: methodology, evaluation, and case study in SAARC countries", *Stochastic Environmental Research and Risk Assessment*, 2023, 37(1), 345–359, https://doi.org/10.1007/s00477-022-02307-x

7. **Jin Y., Wang R., Zhuang X., Wang K., Wang H., Wang C., Wang X.**, "Prediction of COVID-19 Data Using an ARIMA-LSTM Hybrid Forecast Model", *Mathematics*, 2022 Oct 28, 10(21), 4001. https://doi.org/10.3390/math10214001

8. **Tandon, H., Ranjan, P., Chakraborty, T., & Suhag, V.**, "Coronavirus (COVID-19): ARIMA-based time-series analysis to forecast near future" *Journal of Health Management*, 2022, 24(3), https://doi.org/10.1177/09720634221109087

9. **Wang Y., Yan Z., Wang D., Yang M., Li Z., Gong X., Wu D., Zhai L., Zhang W., & Wang Y.**, "Prediction and analysis of COVID-19 daily new cases and cumulative cases: time series forecasting and machine learning models", *BMC Infectious Diseases*, 2022, 22:495, https://doi.org/10.1186/s12879-022-07472-6

10. **Mangla S., Pathak A.K., Arshad M., Haque U.**, "Short-term forecasting of the COVID-19 outbreak in India", *International Health*, 2021 May 27, 13(5), 410–420, https://doi.org/10.1093/inthealth/ihab031

11. **Wang G., Wu T., Wei W., Jiang J., An S., Liang B., Ye L., Liang H.**, "Comparison of ARIMA, ES, GRNN and ARIMA–GRNN hybrid models to forecast the second wave of COVID-19 in India and the United States", *Epidemiology and Infection*, 2021 Oct 21, 149, e240, 1–9. https://doi.org/10.1017/S0950268821002375

12. **Kumar N., Susan S.**, "COVID-19 Pandemic Prediction using Time Series Forecasting Models", In *11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), arXiv preprint*, 2020 Jul 22; arXiv:2009.12176v1, https://doi.org/10.48550/arXiv.2009.12176

13. **Saini V., Richa**, "Prediction of Air Quality Index using time series modelling: A Review Study", *International Journal for Multidisciplinary Research (IJFMR)*, 2025 Mar 14, 7(2), https://doi.org/10.36948/ijfmr.2025.v07i02.38907

14. **Saini V., Richa**, "Analysis of seasonality of Air Quality Index in Muzaffarnagar using the link relative method", *International Journal for Multidisciplinary Research (IJFMR)*, 2025 Jun 28, 7(3), https://doi.org/10.36948/ijfmr.2025.v07i03.49432

15. **World Health Organization (2025)**, *Constitution of the World Health Organization*, World Health Organization, retrieved from https://www.who.int/about/governance/constitution

16. **World Health Organization (2025)**, *COVID-19 Dashboard*, World Health Organization (WHO), retrieved from https://data.who.int/dashboards/covid19/data

17. **Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015)**, *Time Series Analysis: Forecasting and Control* (5th ed.). Wiley.

18. Ministry of Health and Family Welfare **(MoHFW), Government of India (2025)**, *COVID-19 Updates*, retrieved from https://www.mohfw.gov.in/

19. **Saini V., Richa**, "An analysis on general public satisfaction with government healthcare services using linear regression", *International Research Journal of Modernization in Engineering Technology and Science (IRJMETS)*, 2024 Oct, 6(10), https://www.doi.org/10.56726/IRJMETS62351