

# Exploring the Factors behind COVID-19 Surge: Predictive Modeling and Analysis

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**Abstract**— The COVID-19 pandemic has had a significant and unprecedented worldwide influence across the globe, increasing the number of cases and fatalities in various nations. To effectively mitigate and prevent its spread, it is crucial to comprehend the various factors contributing to its transmission. This research paper aims to address this issue by exploring the data collected from official sources in India, which includes variables such as temperature, humidity, air quality index, demographic characteristics, medical history, and lifestyle choices. We aim to use predictive modelling approaches to explore the connection between numerous parameters and the number of COVID-19 cases in the Delhi-NCR region. The dataset's characteristics were identified through exploratory data analysis, and subsequent modelling processes included feature selection, model training, and evaluation to ensure accurate predictions. A Light Gradient Boosted Machine (LightGBM) model is employed for the analysis. In addition, the influence of demographic characteristics, medical and surgical history, smoking and alcohol habits, and an athletic lifestyle on COVID-19 patients is also investigated. The findings of this study contribute to understanding the various dynamics of COVID-19 transmission and may be used to design specific treatments and public health initiatives for effective control and prevention.

**Keywords**— COVID-19, Predictive Modeling, Forecasting, LightGBM, Data Analysis.

## I. INTRODUCTION

The epidemic of the new coronavirus SARS-CoV-2 has resulted in a global health catastrophe, impacting millions of people worldwide and stretching healthcare systems to their limits. COVID-19 is mostly spread by inhaling droplets, which are made when a sick person sneezes, breathes, coughs, or speaks. Close contact with sick persons, particularly in crowded indoor settings, significantly increases the chance of transmission. The high transmissibility of COVID-19 has led to community spread, where the virus circulates within the population without a clear source of infection. In the wake of the initial outbreak of COVID-19 in late 2019, the virus has spread swiftly over the world, causing severe illness, a high mortality rate, and unprecedented disruptions to societal and economic activities worldwide.

India is one among the countries most afflicted by the epidemic, with Delhi NCR being one of the most affected regions. The region's densely populated areas, coupled with the high transmissibility of the virus, have contributed to

community transmission, and increased the risk of infection. Ensuring sufficient healthcare system capacity is essential for managing and providing adequate care to COVID-19 patients. Governments, healthcare organizations, and scientists have been striving to gain a better insight into the virus' transmission dynamics and identify key factors driving the surge in cases. Accurate forecasting and analysis of these factors can provide valuable insights for public health interventions, resource allocation, and policymaking.

In this research, we leverage predictive modelling techniques to understand the relationships between various parameters, the rise in the number of cases, and the spreading patterns of COVID-19. We collect a dataset from various government sources, including information on temperature, humidity, air quality index, demographic characteristics, medical history, surgical history, and lifestyle habits. In this research, we employ a dataset covering the period from January 2020 to December 2022, encompassing three years of data. Exploratory data analysis techniques are applied to gain insights into the distribution and patterns within the dataset, facilitating the identification of potential relationships between variables. We employ various modelling techniques to analyze and predict COVID-19 cases, including regression models, decision trees, and time series analysis. These models are applied to identify significant relationships between the variables selected and the frequency of COVID-19 cases. Among these models, the LightGBM model consistently demonstrates superior performance, providing accurate predictions and valuable insights.

The LightGBM model is a powerful machine-learning algorithm known for its efficiency and effectiveness in handling large datasets. Feature selection techniques are applied to identify the most influential variables driving the surge in COVID-19 cases, aiding in understanding the underlying factors and their impact. We conduct multiple sensitivity analysis tests to gauge the impact of the individual parameters on the number of COVID-19 cases in the Delhi-NCR region. The findings of our investigation show that past medical history, followed by climate variables, has the most significant influence on the number of cases. Demographic information, including age groups, gender, and occupation, also affects the number of cases. The conclusions of this research may assist public health authorities, lawmakers, and medical specialists build realistic methods to restrict the virus's spread and lessen its adverse influence on the population.

## II. LITERATURE SURVEY

COVID-19's proliferation has resulted in an unparalleled worldwide health disaster, necessitating the discovery of critical variables driving its transmission. This literature review focuses on previously done research that analyses how various environmental, demographic, lifestyle, and medical variables might influence the incidence rate of COVID-19 patients across diverse geographical areas.

Liu et al. examined the atmospheric properties of SARS-CoV-2 and reported low concentration of viral RNA in hospital wards but larger amounts in patient toilet regions. They suggested the potential for aerosol transmission and emphasized the importance of ventilation and sanitization [1]. Morawska and Cao emphasised the airborne dispersion of COVID-19 in confined situations. They emphasized the need to acknowledge this route of infection and recommended ventilation as a control measure [2]. Kumari et al. proposed a mathematical model, SEIAQRDT, which accurately predicted COVID-19 cases by considering asymptomatic individuals. Their model improved control strategies by classifying infected individuals based on symptoms [3]. A compartmental model was created by Khajanchi et al. to study Covid-19 transmission in India. They estimated model parameters, performed short-term predictions, and investigated optimal control strategies to reduce transmission [4]. Juneja et al. studied the effect of external factors on COVID-19 spread in Delhi, Kerala, and Tamil Nadu. Their analysis considered temperature and humidity as influencing factors for policymakers [5].

Several studies highlight the relationship between weather patterns and the transmission of the virus. The study by Gupta et al. (2020) examines the influence of climate on COVID-19 cases in India and finds that transmission is subject to a specific climate pattern. [6]. Similar results are revealed by Bashir et al. (2020), who analyse the association between meteorological conditions and COVID-19 in the US capital and conclude that air quality, minimum temperatures, and average temperatures are all highly connected to the pandemic [7]. The COVID-19 pandemic has also had significant environmental impacts. Hammad et al. (2023) discuss the positive effects of the pandemic, such as reduced air, water, and noise pollution, but also highlight negative impacts, such as increased release of microcontaminants and biomedical waste generation [8]. Additionally, the pandemic has affected various aspects of society, including the social dimension. Goswami and Neog (2023) explore the social consequences of COVID-19, including psychological effects, social crises, and emerging trends in the social economy [9, 10, 11].

Air quality has been a significant concern during the pandemic. Ali and Islam (2020) study the effects of air pollution on COVID-19 illnesses and death, focusing on the role of PM2.5 and nitrogen dioxide in higher infection and mortality rates [12]. Another study by Kaloni et al. (2022) analyzes the implications of the COVID-19 lockdown on the air's cleanliness in New Delhi, India, and finds a large drop in pollution amounts during the restricted period [13]. Finally, the article by Kumar, Khandelwal, and Gadhwal (2022) discusses the nexus between global environmental problems, climate change, human health, and COVID-19. It emphasizes the critical need for mitigation solutions to address the difficulties presented by climate change to human health, food, and water security, and contamination of the environment [14]. The COVID-19 pandemic's non-

pharmaceutical interventions (NPIs) are thoroughly reviewed by Perra (2021). The study covers various aspects, such as travel restrictions, social isolation, and lockdowns, showing the effect of these measures on disease spread. In addition, the study analyzes a wide range of literature to understand the effectiveness of NPIs and provides insights into future challenges and opportunities [15].

Several studies focus on predictive modeling to aid in COVID-19 detection and forecasting [16, 17, 18, 19, 20, 21, 22, 23]. Abirami and Kumar (2022) compare machine-learning models for disease detection and prediction. They discovered that supervised learning approaches, particularly classification models, are more accurate than unsupervised learning methods in predicting COVID-19 [16]. Shinde et al. (2020) provides a review of forecasts models for COVID-19. It discusses the role of various parameters in pandemic forecasting and addresses technical and generic challenges associated with these approaches [17]. Kumar and Susan (2020) focus on time series projection models, especially ARIMA and Prophet, to predict the spread of COVID-19. They assess the effectiveness of the models using different error metrics and indicate that the ARIMA model is more efficient for predicting the rate of COVID-19 frequency [18]. Mandayam et al. (2020) use regression models, specifically Linear Regression and Support Vector Regression, to forecast future COVID-19 cases [19]. Machine learning techniques are used by Malki et al. (2021) to forecast the propagation of COVID-19. Their proposed model accurately predicts proven cases and suggests that COVID-19 infections will greatly drop in the first week of September 2021 [20].

Rajan Gupta, Pandey, and Pal (2021) perform a comparison study of different demographic and machine/deep learning models for COVID-19 forecasts. They evaluate these models using different evaluation criteria across ten regions and provide insights into the suitability of different models based on the flattening of cases and growth curve patterns [21]. Univariate and multivariate time series models were discussed for COVID-19 forecasting by Sreehari et al. in 2021. They find that multivariate time series models outperform univariate models, especially for long-term predictions [22]. Finally, Vasudev et al. (2022) propose an ensemble of deep-learning models for epidemic outbreak prediction, explicitly focusing on COVID-19. Their study highlights the importance of using technology and forecasting techniques to mitigate the pandemic's impact [23].

## III. PROPOSED METHODOLOGY

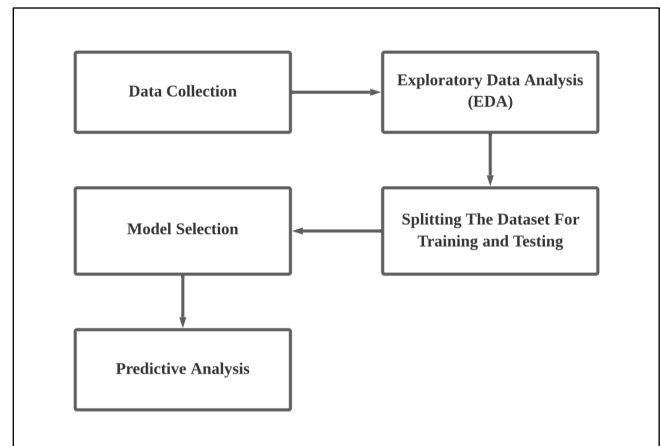


Fig. 1. Schematic Flow Diagram For Proposed Methodology

The proposed methodology for this research aims to comprehensively investigate the various factors contributing to the surge in COVID-19 cases. This study focuses on variables like temperature, humidity, air quality index, senior citizen population, gender diversity, labor/hazardous work percentage, prior medical and surgical history, cardiovascular disease, gastrointestinal disease, smoking/alcohol habit, and the athletic individual's percentage. It involves several steps [Fig 1], from collecting and preprocessing data to evaluating results.

### A. Data Collection & Preprocessing

The data was collected from recognized international organizations like the World Health Organisation (WHO) and official sources within the Indian government, including statistics and health departments. The collected data included parameters such as temperature, humidity, air quality index, senior citizen population, gender diversity, labor/hazardous work percentage, prior medical and surgical history, cardiovascular and gastrointestinal diseases, smoking and alcohol habits, and the athletic individual's percentage. This dataset covers a significant period of the COVID-19 pandemic, ranging from January 2020 to December 2022.

Before modeling, any dataset abnormalities must be identified and corrected to achieve the best performance. In this research, the dataset underwent preprocessing to handle outliers, missing data, and other irregularities. The dataset's null values were first replaced with the median values for the associated feature as part of the preparation procedure. Additionally, data augmentation techniques were employed to ensure a robust testing dataset. Data augmentation also helped to ensure accurate and reliable predictions without overfitting the dataset. After the data preprocessing and augmentation steps, the dataset was ready for our analysis. [Fig 2] illustrates a segment of the dataset, offering a glimpse into its overall structure and characteristics.

DATE	TEMPERATURE	HUMIDITY	AIR QUALITY INDEX	SENIOR CITIZEN (%)	GENDER DIVERSITY (MALE : FEMALE) %	LABOUR / HAZARDOUS WORK (%)	PRIOR MEDICAL HISTORY (%)	PRIOR SURGICAL HISTORY (%)	CARDIOVASCULAR DISEASE (%)	GASTRO-INTESTINAL DISEASE (%)	SMOKING / ALCOHOL HABIT (%)	ATHLETIC PERSON (%)	NUMBER OF COVID-19 CASES
2020-04-01	24.4	58.4	90	6.477079	63.728738	15.640726	17.284708	5.028437	5.894751	4.321189	0.827448	3.088129	55
2020-04-02	24.5	52.8	77	11.347782	43.851476	15.476381	15.074836	5.490447	5.621577	5.177675	1.004137	2.934016	67
2020-04-03	23.6	44.2	93	3.596084	54.745846	29.971260	22.309864	8.463380	2.09124	4.985242	1.893967	2.422286	100
2020-04-04	24.5	45.7	102	10.640119	43.883067	17.925382	10.840782	18.420036	5.130626	6.898100	4.461548	5.000726	126
2020-04-05	25.9	45.7	117	4.231188	53.344369	16.799106	14.629100	6.025953	3.947803	4.120617	0.956768	2.479541	68
2020-04-06	28.2	44.6	122	9.725094	54.046790	15.285486	16.979693	6.020472	5.656211	5.834982	1.380362	4.295044	20
2020-04-07	26.6	46.7	94	9.965386	41.731963	14.402382	16.194867	6.097947	6.341363	3.106919	0.838867	4.921995	53
2020-04-08	26.4	40.6	101	4.895206	56.527256	10.331037	15.263409	9.018919	5.948637	5.545886	2.232041	4.257838	69
2020-04-09	25.6	41.9	101	6.337678	58.220637	14.574158	11.935973	5.733537	4.930100	5.498332	1.480095	2.064839	73
2020-04-10	27.9	39.0	127	6.618576	46.192873	17.133847	14.644490	7.645969	3.566767	5.387830	1.022348	4.942468	89

Fig. 2. Time Series Dataset Showing COVID-19 Cases

### B. Exploratory Data Analysis

Understanding the traits and patterns in the dataset is crucially dependent on the exploratory data analysis (EDA). In this study, several key steps were implemented to extract insightful information from the data gathered. The dataset was transformed into a time series format to analyze the temporal aspects of the data. Graphs and visualizations were plotted for each variable [Fig 3], allowing for a better understanding of the trends, patterns, and seasonality present in the data. Standardization techniques, such as scaling the data using methods like StandardScaler(), were applied to bring the variables to a consistent scale. This process ensured that each

variable's contribution to the analysis was unbiased and comparable. To uncover underlying components and trends, seasonal decomposition [Fig 4] was performed, which involved decomposing the time series data into its seasonal, trend, and residual components. This decomposition aided in identifying recurring patterns and understanding the long-term and short-term variations within the data.

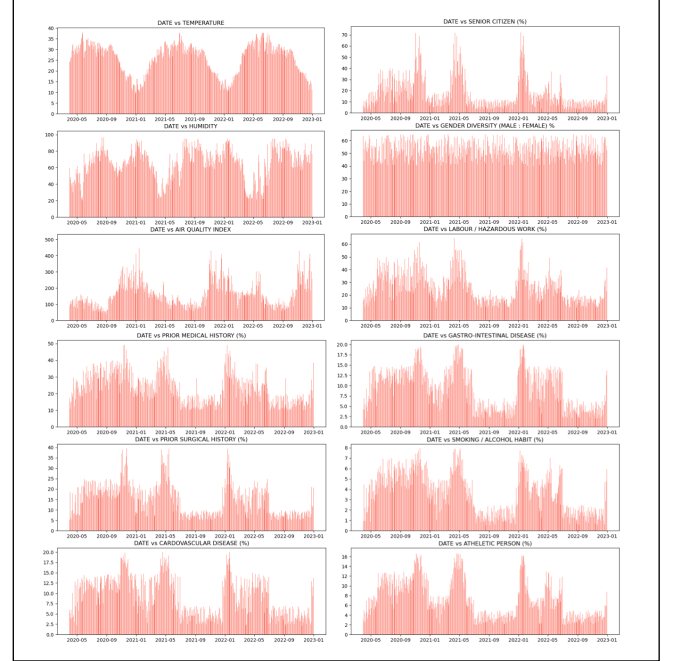


Fig. 3. Data Visualisation

In addition, Principal Component Analysis (PCA), which is a method for reducing dimensionality, was utilized to simplify the dataset while preserving its key characteristics. This approach helped to capture the significant variability within the data and identify the key factors driving the surge in COVID-19 cases. These insights laid the foundation for subsequent modeling and analysis, enabling meaningful interpretations and accurate predictions regarding the factors behind the COVID-19 surge.

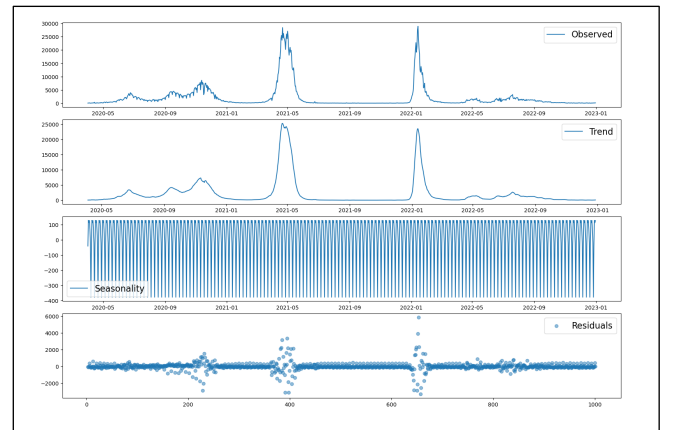


Fig. 4. Seasonal Decomposition of COVID-19 Cases

### C. Splitting The Dataset For Training and Testing

To assess the prediction models' performance and generalization, the dataset was separated into training and testing sets based on key considerations. The testing data was carefully selected to cover a duration of 120 days, ensuring an

adequate representation of different time periods and capturing various trends and patterns within the dataset. This duration allows for a comprehensive evaluation of the model's aptitude to forecast COVID-19 cases over a meaningful time span. The training set, comprising the remaining data, was utilized for training the models on historical patterns and relationships, enabling them to learn and capture the underlying dynamics. By conducting rigorous testing on the independent testing set, the model's performance can be accurately assessed, including its ability to generalize to unseen data and handle future scenarios. The splitting of the dataset for training and testing strikes a balance between capturing temporal dependencies and providing a robust evaluation framework, ultimately enhancing the reliability and applicability of the research findings.

#### D. Model Selection

The selection of an appropriate model is a critical step to accurately predict COVID-19 cases and analyze the factors driving the surge. Different models were assessed for their performance and applicability in light of the features of the dataset and the study's goals. Time series analysis, decision trees, regression models, and other machine learning techniques are among the models investigated. However, after thorough consideration, the Light Gradient Boosted Machine (LightGBM) model was determined to be the best option because of its higher performance in handling big datasets, effective computing, and excellent predictive skills. The LightGBM model handles the dataset's temporal nature and accommodates the variables' multidimensionality, making it ideal for capturing complex relationships and interactions. By utilizing the LightGBM model, the research aims to leverage its advanced boosting techniques, such as gradient boosting and decision tree-based learning, to achieve accurate predictions and meaningful insights into the factors behind the COVID-19 surge.

#### E. Predictive Analysis

Utilizing the selected Light Gradient Boosted Machine (LightGBM) model, the goal is to correctly predict COVID-19 cases and gain greater insights into the reasons causing the surge. The trained model, fine-tuned on the training dataset, will be applied to the independent testing dataset to assess its performance in predicting future COVID-19 cases. The model's predictions will shed light on the multifaceted dynamics of COVID-19 transmission, aiding in the development of targeted treatments, public health interventions, and resource allocation strategies. The findings of the predictive analysis will contribute to evidence-based decision-making, enabling effective control and prevention of COVID-19.

### IV. RESULTS

The prediction modeling and analysis performed in this study provide useful insights into the factors adding to the surge in COVID-19 cases in the Delhi-NCR region. The results show important connections and trends that help in understanding the dynamics of COVID-19 spread and guide tailored medicines, public health measures, and resource allocation techniques. It is found that temperature has a substantial effect on COVID-19 cases [Fig 5]. The research also identified previous medical history, climate variables, and labor/hazardous work percentage as the most determining

factors. The analysis of demographic data of COVID-19 patients reveals that elderly individuals are more susceptible to the virus. Additionally, smoking and alcohol habits, as well as a lack of physical activity, have a direct impact on the virus' transmission. The LightGBM model is employed to predict the number of cases and evaluate the predictive power of the dataset. In this paper, the model's performance is measured in the terms of mean absolute error(MAE) [Fig 6], mean squared error(MSE), and R-Squared(R<sup>2</sup>). The model is applied to the testing dataset after being trained on the training dataset, and it performs excellently with an accuracy of 95.4%.

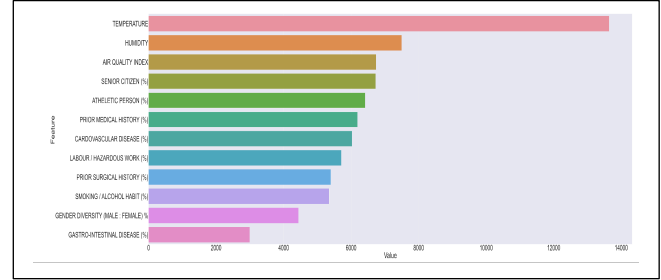


Fig. 5. LightGBM Model Features Importance

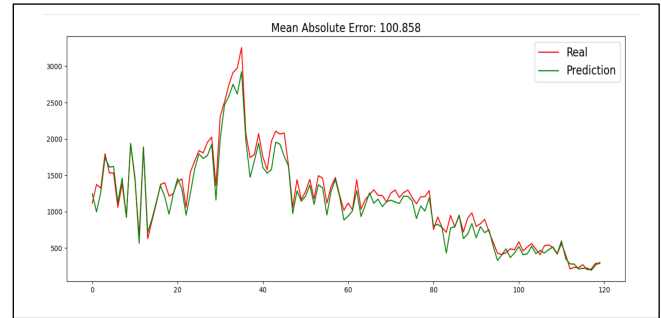


Fig. 6. Real v/s Prediction

### V. DISCUSSION & FUTURE WORKS

The analysis of the dataset revealed several important findings regarding the factors influencing the surge in COVID-19 cases. These findings can serve as a foundation for further research and analysis.

- **Integration of additional variable:** While this study considered a wide range of variables, there may be other elements that add to the spread of COVID-19. Future studies could explore the inclusion of variables such as vaccination rates, mobility data, and socioeconomic indicators to gain a more comprehensive understanding of the pandemic's dynamics.
- **Evaluation of intervention strategies:** The prediction models can be expanded to assess the effectiveness of different intervention strategies, such as lockdown measures, mask requirements, and vaccine programmes. By incorporating data on these interventions, policymakers can make informed decisions regarding the implementation and timing of various measures.
- **Regional analysis:** This research focused on the Delhi-NCR region; however, different regions may exhibit distinct patterns and factors contributing to COVID-19

transmission. Future work could involve expanding the analysis to other regions within India or even globally, allowing for a more nuanced understanding of the pandemic's impact.

- Long-term predictions: The predictive analysis in this research covered a 120-day testing period. Extending the prediction horizon to longer timeframes can provide insights into the potential trajectory of the pandemic and facilitate proactive planning and resource allocation.

## VI. CONCLUSION

This research paper successfully explored the factors behind the surge in COVID-19 cases through predictive modeling and analysis. By utilizing a diverse set of variables, the study shed light on the multifaceted dynamics of COVID-19 transmission. The Light Gradient Boosted Machine (LightGBM) model proved to be an effective tool for accurately predicting COVID-19 cases and capturing complex relationships within the dataset. The findings contribute to evidence-based decision-making by informing targeted treatments, public health interventions, and resource allocation strategies. The future works outlined above can further enhance our understanding of the pandemic and facilitate the development of proactive and effective measures to control and prevent COVID-19. By continuing to analyze and explore the factors influencing transmission, we can better protect public health and mitigate the impact of the pandemic.

## REFERENCES

- [1] Liu, Y., Ning, Z., Chen, Y. et al. Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals. *Nature* 582, 557–560 (2020). <https://doi.org/10.1038/s41586-020-2271-3>
- [2] Lidia Morawska, Junji Cao, Airborne transmission of SARS-CoV-2: The world should face the reality, *Environment International*, Volume 139, 2020, 105730, ISSN 0160-4120, <https://doi.org/10.1016/j.envint.2020.105730>
- [3] Kumari, P., Singh, H.P. & Singh, S. SEIAQRDT model for the spread of novel coronavirus (COVID-19): A case study in India. *Appl Intell* 51, 2818–2837 (2021). <https://doi.org/10.1007/s10489-020-01929-4>
- [4] Khajanchi, S., Sarkar, K. & Banerjee, S. Modeling the dynamics of COVID-19 pandemic with implementation of intervention strategies. *Eur. Phys. J. Plus* 137, 129 (2022). <https://doi.org/10.1140/epjp/s13360-022-02347-w>
- [5] Juneja, N., Sunidhi, Kaur, G., Kaur, S. (2022). Impact of Environmental Factors on COVID-19 Transmission Dynamics in Capital New Delhi Along with Tamil Nadu and Kerala States of India. In: Dua, M., Jain, A.K., Yadav, A., Kumar, N., Siarry, P. (eds) *Proceedings of the International Conference on Paradigms of Communication, Computing and Data Sciences. Algorithms for Intelligent Systems*. Springer, Singapore. [https://doi.org/10.1007/978-981-16-5747-4\\_36](https://doi.org/10.1007/978-981-16-5747-4_36)
- [6] Gupta, A., Pradhan, B. & Maulud, K.N.A. Estimating the Impact of Daily Weather on the Temporal Pattern of COVID-19 Outbreak in India. *Earth Syst Environ* 4, 523–534 (2020). <https://doi.org/10.1007/s41748-020-00179-1>
- [7] Bashir MF, Ma B, Bilal, Komal B, Bashir MA, Tan D, Bashir M. Correlation between climate indicators and COVID-19 pandemic in New York, USA, *Science of The Total Environment*, Volume 728, 2020, 138835, ISSN 0048-9697, <https://doi.org/10.1016/j.scitotenv.2020.138835>
- [8] Hammad, H.M., Nauman, H.M.F., Abbas, F. et al. Impacts of COVID-19 pandemic on environment, society, and food security. *Environ Sci Pollut Res* (2023). <https://doi.org/10.1007/s11356-023-25714-1>
- [9] Goswami, R., Neog, N. (2023). COVID-19: An Insight into Social Dimension. In: *The Handbook of Environmental Chemistry*. Springer, Berlin, Heidelberg. <https://doi.org/10.1007/978-2023-996>
- [10] Parvin R. A Statistical Investigation into the COVID-19 Outbreak Spread. *Environmental Health Insights*. 2023;17. doi:10.1177/11786302221147455
- [11] Venkatesh S Amin, Dr. Abhishek N, Dr. Abhinandan Kulal et al. Covid-19 and Dynamic Changes in Learning Environment: A Perceptual Study, 09 January 2023, PREPRINT (Version 1) available at Research Square. <https://doi.org/10.21203/rs.3.rs-2454785/v>
- [12] Ali N, Islam F. The Effects of Air Pollution on COVID-19 Infection and Mortality-A Review on Recent Evidence. *Front Public Health*. 2020 Nov 26;8:580057. <https://doi.org/10.3389/fpubh.2020.580057>
- [13] Dewansh Kaloni, Yee Hui Lee, Soumyabrata Dev, Air quality in the New Delhi metropolis under COVID-19 lockdown, *Systems and Soft Computing*, Volume 4, 2022, 200035, ISSN 2772-9419, <https://doi.org/10.1016/j.sasc.2022.200035>
- [14] Kumar, A., Khandelwal, S.G., Gadhwal, N. (2022). Global Environmental Problems: A Nexus Between Climate, Human Health and COVID 19 and Evolving Mitigation Strategies. In: Arora, S., Kumar, A., Ogita, S., Yau, Y.Y. (eds) *Innovations in Environmental Biotechnology*. Springer, Singapore. [https://doi.org/10.1007/978-981-16-4445-0\\_3](https://doi.org/10.1007/978-981-16-4445-0_3)
- [15] Perra N. Non-pharmaceutical interventions during the COVID-19 pandemic: A review. *Phys Rep*. 2021 May 23;913:1-52. <https://doi.org/10.1016/j.physrep.2021.02.001>
- [16] Abirami RS, Kumar GS. Comparative Study Based on Analysis of Coronavirus Disease (COVID-19) Detection and Prediction Using Machine Learning Models. *SN Comput Sci*. 2022;3(1):79. <https://doi.org/10.1007/s42979-021-00965-2>
- [17] Shinde GR, Kalamkar AB, Mahalle PN, Dey N, Chaki J, Hassanien AE. Forecasting Models for Coronavirus Disease (COVID-19): A Survey of the State-of-the-Art. *SN Comput Sci*. 2020;1(4):197. <https://doi.org/10.1007/s42979-020-00209-9>
- [18] N. Kumar and S. Susan, "COVID-19 Pandemic Prediction using Time Series Forecasting Models," 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2020, pp. 1-7, <https://doi.org/10.1109/ICCCNT49239.2020.9225319>
- [19] A. U. Mandayam, R. A.C, S. Siddesha and S. K. Niranjana, "Prediction of Covid-19 pandemic based on Regression," 2020 Fifth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), Bangalore, India, 2020, psp. 1-5, <https://doi.org/10.1109/ICRCICN50933.2020.9296175>
- [20] Malki, Z., Atlam, ES., Eweis, A. et al. The COVID-19 pandemic: prediction study based on machine learning models. *Environ Sci Pollut Res* 28, 40496–40506 (2021). <https://doi.org/10.1007/s11356-021-13824-7>
- [21] Rajan Gupta, Gaurav Pandey & Saibal K. Pal (2021) Comparative analysis of epidemiological models for COVID-19 pandemic predictions, *Biostatistics & Epidemiology*, 5:1, 69-91, <https://doi.org/10.1080/24709360.2021.1913709>
- [22] K. Sreehari, M. Adham, T. D. Cheriya and R. Sheik, "A Comparative Study between Univariate and Multivariate Time Series Models for COVID-19 Forecasting," 2021 International Conference on Computational Performance Evaluation (ComPE), Shillong, India, 2021, pp. 485-491, <https://doi.org/10.1109/ComPE53109.2021.9752079>
- [23] R. Vasudev, P. Dahikar, A. Jain and N. Patil, "Epidemic Outbreak Prediction with Ensemble of Deep Learning Models," 2022 IEEE 7th International Conference on Recent Advances and Innovations in Engineering (ICRAIE), MANGALORE, India, 2022, pp. 71-76, <https://doi.org/10.1109/ICRAIE56454.2022.10054258>