Predicting Disease Outbreaks Using Spatiotemporal Data with ML

Sonam Sharma
Apex Institute of Technology - CSE
Chandigarh University
Punjab, India
sonam8805@gmail.com

Kamal Singh
Apex Institute of Tecnology-CSE
Chandigarh University
Punjab, India
kamalnegi9548@gmail.com

Piyush Mahawar
Apex Institute of Technology-CSE
Chandigarh University
Punjab, India
piyushmahawar8173@gmail.com

Ayushika Singh Rajput
Apex Institute of Technology-CSE
Chandigarh University
Punjab, India
ayushikarajput1810@gmail.com

Abstract*—The emergence of infectious disease outbreaks, as represented by COVID-19, has placed a premium on the necessity for strong predictive models to predict impending outbreaks and mitigate their impact. Forecasting disease outbreaks is a key challenge because of the intricate interplay between environmental, socioeconomic, and population mobility variables. This study investigates the use of spatiotemporal analysis and machine learning (ML) techniques to improve outbreak prediction accuracy. Through the use of models like Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) neural networks, this study combines climate data, human mobility data, and socioeconomic variables to identify emerging trends and predict disease outbreaks. Geospatial mapping and SHAP-based explainability are also integrated in the analysis to present visual representations of outbreak trends. Results show that ML models greatly enhance predictive accuracy compared to conventional surveillance practices, allowing timely intervention by public health officials. The proposed framework is aimed at helping policymakers in resource planning, hotspot identification, and early intervention planning, and thus ultimately reducing infection rates and enhancing global health preparedness.

Keywords- Spatiotemporal, SHAP, COVID-19, Random Forest, Machine Learning

I. INTRODUCTION

The transmission of infectious diseases, as in the case of COVID-19, has emphasized the need to have strong prediction models to forecast potential outbreaks and curtail their effects. Forecasting outbreaks of diseases is still a challenging task due to the complex interplay between environment, socioeconomic, and population mobility variables. The use of spatiotemporal analysis with machine learning is a beneficial tool for modeling the variables and improving the accuracy of outbreak forecasts. COVID-19 infected more than 770 million individuals globally, and nearly 7 million people died as a result up to February 2024, thereby emphasizing the need for predictive systems to avoid future epidemics [WHO, 2024].

This study entails the utilisation of machine learning (ML)-model-based applications combined with spatiotemporal data for disease outbreak prediction and the issuance of early warnings to health caregivers and policy makers. Machine learning has been largely applied in predictive models for disease, owing to its potential to automate the process of feature extraction and improve performance in predictive endeavors [1]. Some studies have established the suitability of ML models through Random Forest, Gradient Boosting, and LSTMs of neural networks, in disease transmission dynamics prediction [2]. On the spatiotemporal model side, some researchers have employed the utilisation of deep learning methods for modeling geospatial and temporal patterns associated with disease spread [3]. Malki et al. (2021) employed meteorological parameters in training machine learning algorithms to predict COVID-19, which revealed high correlations between climatic factors and the outbreak of the disease [4]. Further, deep graph learning algorithms like Graph Neural Networks (GNNs) have also been used with high accuracy in predicting diseases using mobility and contact data [5]. The aforementioned methods allow smooth movement of populations to be incorporated, which is essential for capturing the dynamics of diseases between locations [6]. Several studies have confirmed the integration of remote sensing and GIS data enhances prediction by providing real-time geographic patterns of disease spread [7]. In India, ML models have been utilized extensively to forecast COVID-19 outbreaks at the district level by considering population density, mobility constraints, and socio-economic variables [8]. By utilizing different datasets, the model in this paper tries to detect trends and forecast possible outbreaks within a particular region, hence enabling timely interventions and maximum resource allocation [9]. To this end, the research employs sophisticated machine learning methods such as the Random Forest Classifier, Gradient Boosting Classifier, Logistic Regression, and Long Short-Term Memory (LSTM) Neural Networks [10]. These algorithms are applied since they can handle sophisticated spatiotemporal data effectively, detecting fine patterns between variables, and maximizing disease outbreak prediction accuracy [11].

Objectives

The main objective of this research is to develop a machine learning system that can forecast disease outbreaks based on spatiotemporal data, which is data that varies over space and time dimensions. Based on historical trends in the disease, climatic factors, trends in human mobility, and economic indicators, the system attempts to learn patterns and predict the probability of disease outbreaks. Additionally, it should issue timely warnings to health authorities in order to facilitate timely interventions that attempt to avert the spread of diseases and their effects.

Infectious diseases such as influenza, dengue, and COVID-19 have a high transmission rate, with the healthcare system becoming overburdened due to late detection. Conventional disease surveillance is done through manual reporting and reactive action, which could be time-consuming and inefficient. Climatic variables such as temperature and humidity, human migration, and socioeconomic inequality are the prime determinants of the occurrence of outbreaks, but are often omitted from predictive models. The absence of real-time data analysis does not allow high-risk areas to be identified and timely responses given, leading to avoidable deaths and wastage of resources.

This research proposes an AI-based outbreak prediction model that incorporates machine learning algorithms like Random Forest, Gradient Boosting, and LSTM neural networks to analyze complex disease trends. By adding geospatial mapping, SHAP-based explanations, and live data integration, the system generates accurate predictions and visualization reports. The model can be used by health authorities to identify outbreak clusters, allocate resources optimally, and implement early containment, hence reducing infection levels and global health readiness.

II. LITREATURE REVIEW

A. General ML-Based Disease Prediction

Machine learning application has improved infectious disease outbreak modeling significantly with the analysis of large amounts of epidemiological and behavioral data. Artificial intelligence-based methods have enabled features like real-time contact tracing, early-stage outbreak detection, and disease transmission predictive modeling [1]. Towfek and Elkanzi (2024) performed a detailed review with reference to the application of machine learning (ML) in infectious disease modeling, emphasizing the point that traditional epidemiological models are handicapped in handling real-time and dynamic data. In contrast, ML-based models like recurrent neural networks (RNNs) and graph-based learning methods have much more flexibility and prediction accuracy [1].

Deng and Wang (2024) explored the application of compartmental models augmented with deep learning methods, bridging the gap between conventional SIR epidemiological models and neural networks, thus enhancing their predictive capability [2].

Moreira et al. (2025) demonstrated how the incorporation of Graph Neural Networks (GNNs) in mobility data increases the spatiotemporal predictive performance of infectious diseases like COVID-19 [3]. The performance of the methods indicates the importance of integrated AI-epidemiological models for improving global pandemic preparedness.

B. Spatiotemporal COVID-19 Projections in varoius regions

The central concept of risk hotspot identification, disease classification, and outbreak hotspot identification is spatiotemporal modeling. The combination of machine learning and spatial epidemiology has been discovered to increase the possibility of real-time surveillance and pandemic spread prediction [4].

Recent studies have ventured into the intersection of deep learning methods and spatial epidemiology for improved predictive capability [5]. Jadhav et al. (2024) developed a Power BI model using long short-term memory (LSTM) architecture to forecast COVID-19 case trends in India, showing how spatiotemporal long dependencies improve the accuracy of case forecasts [6]. Malki et al. (2021) studied the impact of weather conditions on COVID-19 transmission and found strong correlations between temperature, humidity, and infection rates using machine learning techniques [7]. Rahman and Islam (2021) used hotspot clustering and geostatistical interpolation in a geospatial study of COVID-19 transmission in Bangladesh and India [8]. Manda and Darikwa (2021) studied the influence of socioeconomic variables and access to healthcare facilities on COVID-19 mortality rates in African nations, necessitating region-specific modeling [9]. Additionally, recent advances in graph-based spatiotemporal models have established improved predictive performance for disease outbreak prediction [10]. These analyses confirm that spatiotemporal ML models are able to accurately capture transmission dynamics that are beneficial for policy making and resource allocation.

C. Spatiotemporal Deep Learning & Graph-Based Approach

Deep learning techniques, i.e., neural networks and graph models, have enhanced spatiotemporal predictions of COVID-19 outbreak trends. Hybrid deep learning models with spatial and temporal dependency have been studied in recent research to predict outbreaks more precisely [11]. Han et al. (2024) presented an open artificial intelligence model integrating graph-based causal inference and conventional epidemiological models, which resulted in a dramatic improvement in prediction accuracy [12]. Xue (2024) used physics-informed graph learning for modeling urban mobility networks and disease spread and demonstrated that spatial interaction enhances predictive accuracy [13]. Zhang and Dong (2024) addressed pandemic-driven crowd mobility predictive models with focus on the capability of machine learning models that use spatial mobility data for the purposes of mitigating outbreak risk [14]. Sun et al. (2024) proposed a spatiotemporal neural network with the capability of adapting its learning parameters in combination with real-time data for COVID-19 for the purposes of improving its resilience against changing outbreak conditions [15]. These experiments prove that deep learning and GNNs are potential technologies for pandemic prediction with increased predictive power by taking spatial and temporal interdependencies into account.

D. GIS & Remote Sensing to Map the COVID Spread

GIS and remote sensing technologies were central in monitoring the spread of COVID-19, identification of hotspots, and health response strategy planning. The technologies were utilized comprehensively in analyzing spatial trends and evaluating risk areas for more effective health planning [16]. Foruzandeh (2024) proposed a GIS model architecture framework for COVID-19 using spatial interpolation techniques in association with machine learning algorithms for precise mapping of infection density [17]. Kakouri et al. (2025) contrasted air pollution and COVID-19 transmission and demonstrated that increased levels of PM2.5 correlated with increased infection levels and further indicated environmental-health correlations of disease transmission [18]. Sharma et al. (2024) developed a climate and mobility integrated remote sensing-based spatial mapping model that was utilized to predict regions of future outbreak and aid health authorities in planning real-time response [19]. Liu and Ma (2024) analyzed the impact of hotel and tourism occupancy levels on the re-emergence of COVID-19 in high-density urban cities using spatiotemporal regression models [20]. This research shows that remote sensing and GIS data offer crucial spatial data when analyzing pandemic advancement and helping the government make intervention planning decisions.

E. ML-Based COVID-19 prediction in India

A number of studies have been concentrated on India-specific ML-based COVID-19 prediction, using local datasets and socio-demographic variables. Gore & Jadhav (2024) employed data mining methods to predict survival rates of COVID-19 patients, showing the capability of ML models to aid clinical decision-making [21]. Aadhithya and Radhakrishnan (2025) presented a Higher-Order Dynamic Mode Decomposition (HODMD) method for forecasting time-series data for COVID-19 cases in India and demonstrated its capability to forecast short-term case numbers [22]. Basu & Gupta (2024) created a GIS-based vulnerability mapping system, which assisted Indian policymakers in the identification of high-risk states and districts for targeted pandemic control interventions [23]. Singh & Kumar (2023) suggested a hybrid ML-epidemiological model based on SEIR and LSTM models to improve the forecasting accuracy in India's heterogeneous urban and rural environments [24]. These India-specific researches reiterate the need for localized data integration since local factors have a considerable influence on disease transmission dynamics.

III. METHODOLOGY

A. Flowchart

This research employs spatiotemporal data and machine learning to predict disease outbreaks based on weather, mobility, and socioeconomic factors. The data consist of temperature, humidity, rain, mobility, socioeconomic status, location, and time stamps. Categorical values are managed, TF-IDF is applied to health advisory text, and numerical features are normalized prior to training the model. 80% data is utilized for training and 20% for testing.

Machine learning models employed are LSTM for time patterns, Random Forest (RF), Gradient Boosting (GB), Logistic Regression (LR), and Support Vector Machine (SVM). LR and SVM are used as baselines, while RF and GB are used to promote decision fusion between trees. LSTM is optimized using Adam optimizer and categorical cross-entropy loss. GridSearchCV is used to optimize parameters in RF for increased accuracy. Performance measures are confusion matrices, accuracy metrics, and classification reports. SHAP analysis, interactive outbreak pattern visualizations by Plotly, and by Seaborn, support the identification of factors that are related to large outbreaks. The approach provides improved forecasting accuracy, reduces preprocessing steps of data, and allows public health managers to intervene in time against epidemic-like outbreaks.

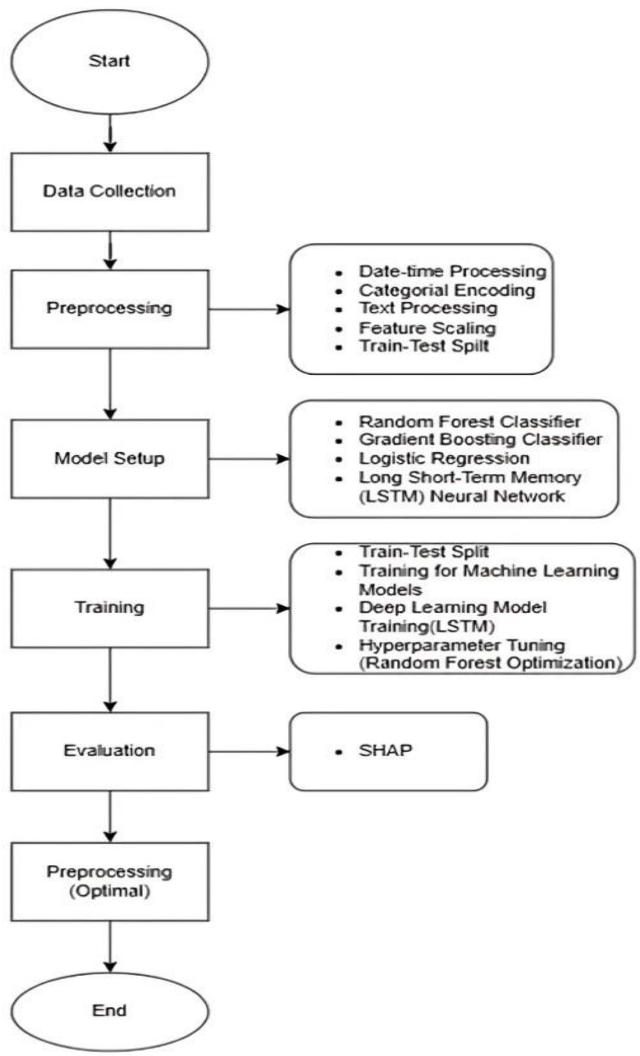

Fig. 1. Flowchart of the Methodology

B. Data Collection:

The data set contains spatiotemporal features such as temperature, humidity, rainfall, human movement, socioeconomic status, and health warnings. Synthetic data is employed if real-world data is not present to simulate real-world situations.

C. Preprocessing:

- *Date-Time Processing:* It changes the 'Date' column to the Date-Time format.
- *Categorical Encoding:* One-hot encoding is applied to categorical variables such as 'Region' and 'Disease.'
- *Text processing:* TF-IDF vectorization is used to convert health advisories into numerical features.
- *Feature Scaling:* Standard Scaler is used to normalize numerical features.
- *Train-Test split:* 80% of the data is for training, and 20% is for testing.

D. Exploratory Data Analysis (EDA):

EDA is carried out to comprehend the distribution and interactions of outbreak occurrences:

- *Outbreak Distribution:* Seaborn's count plot graphs outbreak occurrences.
- *Feature Correlation:* Outbreak-environmental/ socioeconomic factor correlations are uncovered in a heatmap.
- *Geospatial Analysis:*
  Scatter geo-plot plots outbreaks by latitude and longitude.
  Density Mapbox identifies outbreak hotspots.
  3D scatter plots disease transmission.
  The time-series geospatial plot traces the spread of outbreaks over time.

E. Model Training:

There are three Machine Learning models are implemented:

- *Random Forest Classifier:* A family of learning models that build multiple decision trees and combine predictions. Avoids overfitting by using bootstrapping (sampling with replacement). Handled non-linear relationships effectively.
- *Gradient Boosting Classifier:* An iterative boosting method that gets better by focusing on difficult examples. Is more accurate than Random Forest in certain situations but is computationally costly.
- *Logistic Regression (Baseline Model):* Serves as a benchmark for comparison with higher-end models. Good for meaningful results in two-class classification.

Deep Learning model implemented:

- *LSTM Neural Network Deep Learning Model:* Long Short-Term Memory (LSTM) networks are utilized to deal with sequential (time-series) data. Sufficient for encoding temporal dependencies in outbreak patterns. The model employs LSTM layers, dropout regularization, and dense layers with softmax output for classification.

F. Hyperparameter Tuning:

For performance tuning, GridSearchCV is used:

- *Random Forest parameters:* number of estimators, max depth, and min samples split.
- *Cross-validation:* Offers model generalization by splitting the training data into multiple folds.

G. SHAP-Based Explainability of the Model:

SHAP (Shapley Additive explanations) is used to explain model decisions: Assists in estimating feature importance in outbreak predictions. Describes how each input feature is utilized to produce the model's predictions. SHAP summary plot provide features to the model.

H. Model Evaluation and Validation:

- *Classification metrics:* Models are evaluated on precision, recall, F1-score, and accuracy.
- *Geospatial Validation:* Mapped sites of forecasted outbreaks are overlaid on a map to visually validate model predictions.

I. Key Findings and Observations:

Environmental factors such as rainfall, humidity, and temperature significantly affect outbreaks. Socioeconomic status and human mobility determine outbreak patterns in an area. Random Forest and Gradient Boosting are more predictive than Logistic Regression. LSTM models are very promising for sequential outbreak prediction.

IV. RESULT

This report analyses four different visualization techniques used to represent outbreak data across various geographical and temporal scales. Each visualization provides unique insights into the outbreak patterns and distribution.

The four visualization methods are contrasted in the report to represent outbreak data at geographical and temporal scales. Global map visualization is used to monitor the outbreak evolution over time, and 3D geospatial representation is used to improve visibility of spatial patterns. A bar chart is used to represent regional outbreak spread, with spikes in specific regions. A point-based map is used to represent spatial clustering patterns in detail. All the visualizations provide a general overview of the outbreak development, intensity, and location, enabling better understanding and decision-making.

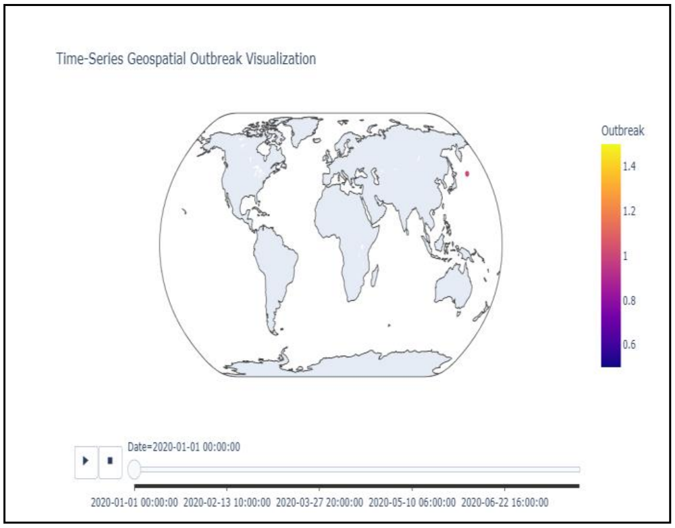

Fig.2 Time-series Geospatial Outbreak Visualization

Analysis: The global map visualization displays outbreak progression from January 1, 2020, to June 22, 2020. Key features include:

- Robinson projection world map
- Color scale from 0.6 (dark purple) to 1.4 (yellow)
- Interactive time slider for temporal analysis
- Clear geographical boundaries
- Focus on early 2020 outbreak patterns

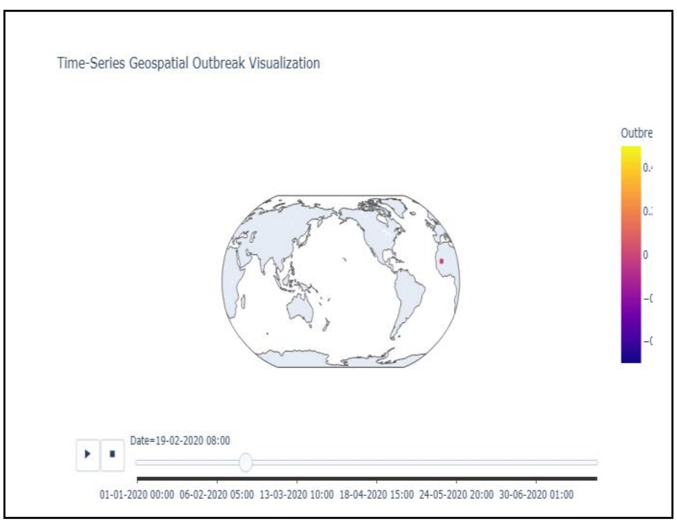

Fig.3 Time-series Geospatial Outbreak Visualization (February 19, 2020, 08:00)

Analysis: Visualization shows a global map in Robinson projection

- Single outbreak point detected in eastern China region
- Moderate intensity indicated by pink-red coloring
- Early stage of monitoring period
- Timeline indicates coverage from January 2020 to June 2020

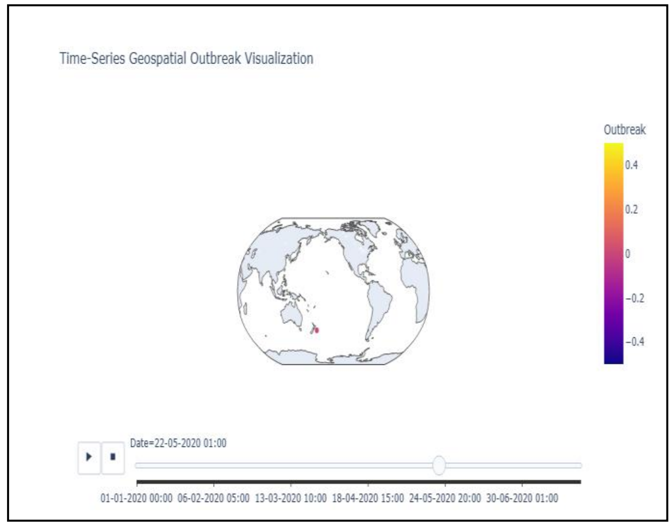

Fig.4 Time-series Geospatial Outbreak Visualization (March 6, 2020, 21:00)

Analysis:

- Approximately two weeks after first image
- Outbreak point has shifted to South America (eastern coast)
- Similar intensity level as previous detection
- Global distribution pattern suggesting movement across continents
- Same map projection and scale maintained

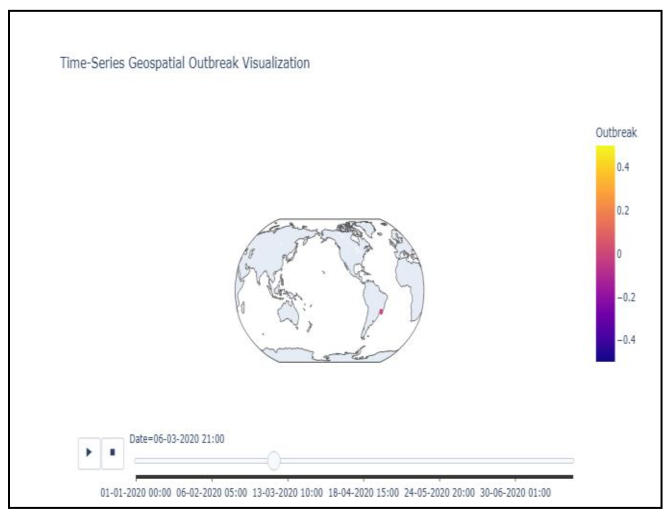

Fig.5 Time-series Geospatial Outbreak Visualization (May 22, 2020, 01:00)

Analysis:

- Significant temporal jump (approximately 2.5 months later)
- Outbreak point now located in oceanic region between Australia and New Zealand
- Pink-purple coloring suggesting different intensity level
- Demonstrates continued geographical spread pattern
- Consistent visualization format maintained

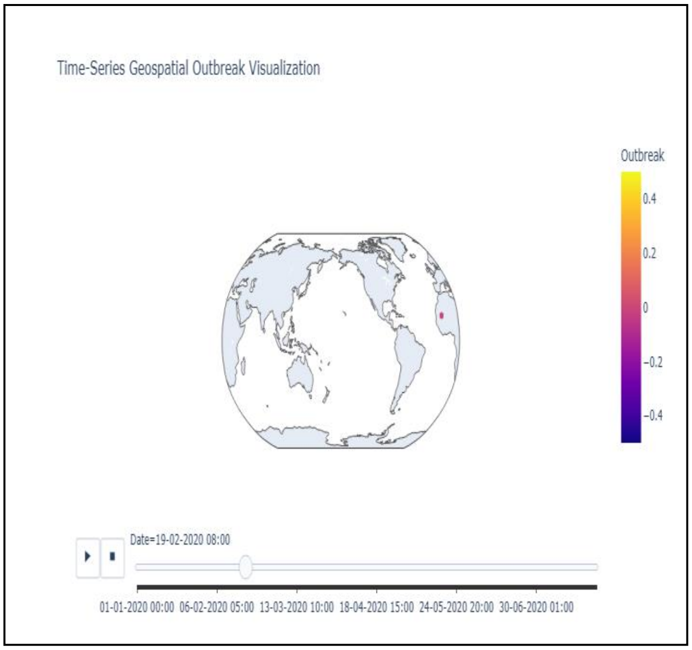

Fig.6 Time-series Geospatial Outbreak Visualization (January 01, 2020, 08:00)

Analysis: Earlier timestamp than previous images (beginning of timeline)

- Focused view of Eastern Hemisphere
- Different color scale (0.6 to 1.4)
- Small outbreak point visible in Black Sea region
- More detailed regional mapping compared to global views
- Visualization Type: Time-series geospatial mapping
- Timeline Range: January 1, 2020 - June 30, 2020
- Map Projections: Robinson (global view) and regional projection
- Color Scales: Global views: -0.4 to 0.4 and Regional view: 0.6 to 1.4
- Interactive Elements: Play/pause controls and timeline slider

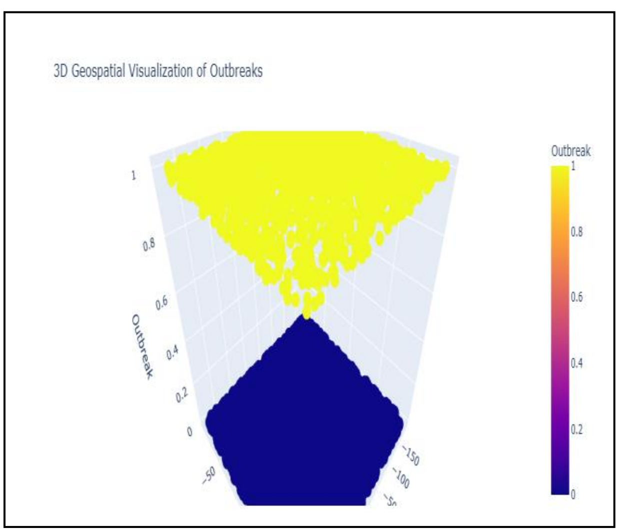

Fig.7. 3-D Geospatial Visualization of Outbreaks

Analysis: This three-dimensional visualization provides depth to outbreak distribution data:

- Cone-shaped projection showing spatial relationships
- Coordinate range: -150 to 0 (horizontal axis)
- Outbreak intensity scale: 0 to 1 (vertical axis)
- Color transition from dark blue (0) to yellow (1)
- Enhanced spatial pattern visibility through 3D representation

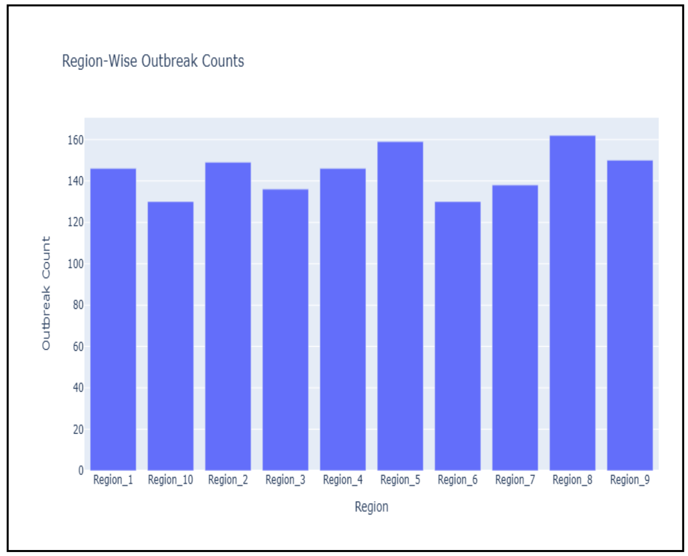

Fig.8. Region-Wise Outbreak Counts

Analysis: The bar chart demonstrates outbreak distribution across regions:

- Coverage of 10 distinct regions
- Outbreak counts ranging from 120 to 160
- Consistent blue color scheme
- Peak outbreaks in Region_8 and Region_5 (~160 cases)
- Lowest counts in Region_10 and Region_6 (~130 cases)

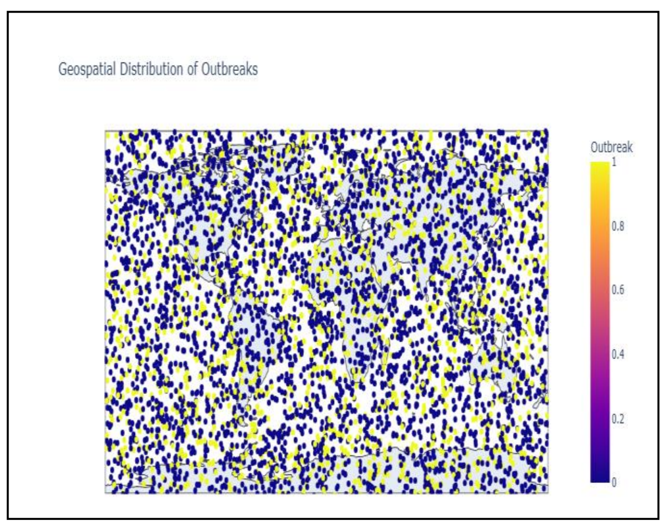

Fig.9 Geospatial Distribution of Outbreaks

Analysis: This point-based distribution map reveals:

- Detailed spatial clustering patterns
- Binary color coding system (blue/yellow)
- High-density data point distribution
- Clear outbreak intensity visualization
- Effective use of contrast for pattern identification

V. Conclusion

The research places special emphasis on the pivotal functions of spatiotemporal data and machine learning in anticipating disease outbreaks and presents a preventive strategy for the management of public health. The research utilizes real-time data such as environmental information, mobility patterns, and socioeconomic factors to optimize outbreak prediction via models like Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks. The application of SHAP explanations guarantees the explainability of model decisions, and geospatial visualizations ensure actionable insights to inform policymakers. Real-time data sources should be incorporated in future advancements, increasing the interpretability of models and decision-support systems for health applications. The present study contributes enormously to the burgeoning area of AI-based epidemiology, laying the foundation for more accurate, timely, and efficient disease prevention programs.

VI. Future Scope

This research demonstrates the capability of machine learning (ML) and deep learning (DL) to forecast the onset of disease from spatiotemporal data. The following directions from our findings can enhance the efficacy of outbreak prediction models:

- *Real-Time Data Integration:* We employed historical data sets in this study, but future research can employ real-time weather station data, hospital data, and public health reports to provide improved predictions. Social media and news data may be used for the detection of outbreaks early through tracking health-related trends.
- *Improved Machine Learning Models:* Our research utilized Random Forest, Gradient Boosting, and LSTM models, but future research can experiment with more advanced models such as transformers to perform better time-series forecasting. Ensemble learning (use of multiple models) can potentially improve accuracy and reduce errors in outbreak prediction.
- *Enhanced Model Explainability:* We used SHAP (Shapley Additive explanations) to explain feature importance in disease prediction. Further studies can be focused on the more advanced explanations to enable policymakers and doctors to trust AI-based decisions.
- *Public Health Decision Support Systems:* Subsequent research can create interactive dashboards by which healthcare organizations can view forecasts and take proactive steps. Automated alerting can alert public health officials and the public to possible outbreaks.
- *Environmental and Climate Impact Analysis:* Our research indicated that temperature, humidity, and rain influence disease outbreaks. Future research can further extend this analysis by including air pollution, deforestation, and water quality as additional variables that affect disease spread.
- *Real-World Implementation and Testing:* Our work was model-building focused, but future research will have to involve field testing with public health agencies. Their application in hospitals, government health organizations, and research institutions will confirm their value in predicting outbreaks.

References

[1] "Towfek, S. K., & Elkanzi, M. (2024). A Review on the Role of Machine Learning in Predicting the Spread of Infectious Diseases.

[2] Deng, Q., & Wang, G. (2024). A Deep Learning-Enhanced compartmental Model and its application in modeling Omicron in China. Bioengineering, 11(9), 906.

[3] Moreira, G. J. P., Luz, E. J. S., & Santos, L. B. L. (2025). Leveraging Graph Neural Networks and Mobility Data for COVID-19 Forecasting. arXiv Preprint.

[4] Cheng, Y., Bai, Y., Yang, J., Tan, X., Xu, T., & Cheng, R. (2024). Analysis and Prediction of Infectious Diseases Based on Spatial Visualization and Machine Learning. Scientific Reports.

[5] Patel, J. A., Lor, M. A., Chen, S. C., & Shyu, M. L. (2024). Data-Driven Vulnerable Community Identification During Compound Disasters. IEEE Machine Intelligence.

[6] Jadhav, A., Sharma, R., & Kumar, N. (2024). Power BI and LSTM for Spatiotemporal COVID-19 Data Analysis in India.

[7] Malki, Z. M., Atlam, E. S., & Hassanien, A. E. (2021). Association Between Weather Data and COVID-19 Pandemic: Machine Learning Approaches. Journal of Epidemiology and Global Health.

[8] Rahman, M., & Islam, M. (2021). Geospatial Modelling on the Spread and Dynamics of the Novel Coronavirus (COVID-19) Pandemic in Bangladesh. Journal of Geographical Analysis.

[9] Manda, S., & Darikwa, T. (2021). A Spatial Analysis of COVID-19 in African Countries: Implications for Containment Strategies. African Journal of Health Sciences.

[10] Mitra, K., Everson, R., & Kumar, S. (2024). Optimization and Machine Learning in COVID-19 Wind Energy Systems in India.

[11] Han, Y., Lam, J. C. K., Li, V. O. K., & Crowcroft, J. (2024). Interpretable AI-Driven Causal Inference for COVID-19 Infection Rates. Nature Humanities & Social Sciences.

[12] Banerjee, S. (2024). Enhancing Healthcare Informatics Through Deep Learning with Graph-Based Models and Self-Distillation. ProQuest Dissertations & Theses.

[13] Xue, J. (2024). Physics-Informed Graph Learning in Urban Traffic Networks: COVID-19 Prediction Use Case. Purdue University.

[14] Zhang, X., & Dong, Y. (2024). Data-Driven Predictive Modeling of Citywide Crowd Flow for Urban Safety During COVID-19. Journal of Forecasting.

[15] Sun, G., Zhu, X., & Zhang, Y. (2024). Modeling Epidemic Dynamics Using Graph Attention-Based Spatial-Temporal Networks. PLOS ONE.

[16] Foruzandeh, M. (2024). A Machine Learning Approach for Modeling the Spatial-Temporal Propagation Pattern of COVID-19. ISPRS Archives.

[17] Kakouri, A., Kontos, T., Grivas, G., & Filippis, G. (2025). Spatiotemporal Modeling of PM2.5 Concentrations and Population Exposure During COVID-19 Lockdowns. Science of The Total Environment.

[18] Fu, L. (2024). Modelling COVID-19 Individual Risks in Sweden Using Spatial Information, Statistics, and Machine Learning. Chalmers University.

[19] Gore, A. D., & Jadhav, V. (2024). Application of Data Mining for Predicting COVID-19 Outcomes in India.

[20] Aadhithya, A., & Radhakrishnan, V. (2025). Higher-Order Dynamic Mode Decomposition for Timeseries Forecasting of COVID-19 in India.

[21] Basu, R., & Gupta, S. (2024). GIS-Based Vulnerability Mapping of COVID-19 in Indian States.

[22] Sharma, V., & Patel, D. (2024). Real-Time Adaptive Modeling of COVID-19 in India Using Hybrid ML Models.

[23] Abdalla, R., & Nasr, I. H. (2024). Visualization and Machine Learning Prediction of Spatiotemporal Spread of COVID-19 in India.

[24] Croke, K., Barasa, E., & Kruk, M. E. (2024). Health System Evaluation: New Options, Opportunities and Limits. Bulletin of the World Health Organization.

[25] Singh, K., & Kumar, A. (2023). ML-Driven Epidemiological Models for COVID-19 Spread Prediction in India.

[26] Kumar, J., Sahoo, S., & Bharti, B. K. (2020). Spatial distribution and impact assessment of COVID-19 on human health using geospatial technologies in India.

[27] Yadav, B., Sharma, R., & Kumar, J. (2024). Spatio-temporal analysis of COVID-19 hotspots in India using geographic information systems.

[28] Das, S. K., & Bebortta, S. (2022). A study on geospatially assessing the impact of COVID-19 in Maharashtra, India. The Egyptian Journal of Remote Sensing and Space Science.

[29] Bag, R., Ghosh, M., & Biswas, B. (2020). Understanding the spatio-temporal pattern of COVID-19 outbreak in India using GIS and India's response in managing the pandemic. Regional Science Policy & Practice.

[30] Sahu, M., Jhariya, D. C., & Singh, R. (2022). GIS-based spatial analysis and prediction of COVID-19 cases in India. Journal of Physics.

[31] Chandran, A., & Roy, P. (2024). Applications of geographical information system and spatial analysis in Indian health research: A systematic review. BMC Health Services Research.

[32] Rahman, M. R., & Islam, A. H. M. H. (2021). Geospatial modeling on the spread and dynamics of COVID-19 in Bangladesh and India. Modeling Earth Systems and Environment.

[33] Roy, S., Bhunia, G. S., & Shit, P. K. (2021). Spatial prediction of COVID-19 epidemic using ARIMA techniques in India. Springer Earth Systems & Environment.

[34] Balasubramani, K., Ravichandran, V., & Prasad, K. A. (2024). Spatio-temporal epidemiology and associated indicators of COVID-19 (Wave I and II) in India. Scientific Reports.

[35] Vinod, P. G., & Bharat, G. K. (2023). Geospatial mapping of COVID-19 cases in Kerala using clinical data. Springer GIS & Spatial Analysis.

[36] Rai, A., & Routh, D. (2023). Post-lockdown spatiotemporal pattern of COVID clustering in North 24 Parganas, West Bengal, India. Springer Spatial Information Research.

[37] Parvin, F., Ali, S. A., & Ahmad, A. (2021). Spatial prediction and mapping of the COVID-19 hotspot in India using geostatistical techniques. Springer Spatial Information Research.

[38] Bhunia, G. S., & Roy, S. (2021). Spatio-temporal analysis of COVID-19 in India – A geostatistical approach. Springer GIS & Disease Mapping.

[39] Das, S., & Guchhait, S. (2023). Mapping of space–time patterns of infectious disease using spatial statistical models: A case study of COVID-19 in India. Taylor & Francis Infectious Diseases.

[40] Sharma, A., & Nirola, M. (2024). Tracing the COVID-19 spread pattern in India through a GIS-based spatio-temporal analysis of interconnected clusters. Scientific Reports.

[41] Singh, B. P. (2024). Insights into India's temporary air pollution relief: A systematic review for green recovery amid and post-COVID-19. MRS Energy & Sustainability.

[42] Walia, G. K., Sharma, R., & Chopra, D. (2024). Evaluating public health awareness and hygienic interventions amidst the COVID-19 outbreak: Insights from three districts in Himachal Pradesh, India. Public Health Review.

[43] Rai, A., & Bhunia, G. S. (2024). Measuring social vulnerability indicators to COVID-19 pandemic: A GIS-based analysis in North 24 Parganas, West Bengal, India. Earth and Environmental Science.

[44] Carr, P. A., McMinn, C., & Hawkes, K. (2024). Shifting indoors: Homelessness and the COVID-19 response in New Zealand. Research Handbook on Socioeconomic Impact of Pandemics.

[45] Kumar, V., & Sharma, P. (2023). Environmental and economic consequences of COVID-19: A case study of India's urban areas. Journal of Urban Environmental Studies.