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Computational Tracking and Estimating the Covid-19 Dynamic Broadcast Based on Machine Learning Model

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Abstract: The COVID-19 pandemic has reshaped global health and societal norms, necessitating effective tracking and forecasting methods. We propose a novel machine learning model that integrates diverse datasets, including epidemiological, demographic, and environmental variables. By employing advanced techniques such as deep learning and time-series analysis, our model accurately predicts the pandemic's trajectory, considering factors like non-pharmaceutical interventions and variant emergence. Through comprehensive data integration and feature engineering, our approach provides actionable insights for policymakers, aiding in proactive response strategies and adaptive tracking of COVID-19 propagation dynamics.

Keywords : COVID-19 pandemic, Machine learning model, Diverse datasets, Epidemiological, Demographic, Time series analysis, non-pharmaceutical interventions, Data integration, Feature engineering, Adaptive tracking, Propagation dynamics

I. INTRODUCTION

The COVID-19 pandemic, stemming from the novel coronavirus SARS-CoV-2, has profoundly reshaped global dynamics since its emergence in late 2019. With its rapid spread and widespread impact on healthcare systems, economies, and societies, precise tracking and forecasting of virus propagation have become imperative. Consequently, data-driven approaches have gained prominence, with machine learning emerging as a potent tool in this pursuit. This introduction paves the way for an in-depth exploration of an advanced machine learning model tailored for tracking and forecasting COVID-19 propagation dynamics. Leveraging artificial intelligence and diverse data sources, this model promises invaluable insights for healthcare professionals, policymakers, and the public. Amidst the complex transmission dynamics of COVID-19, characterized by evolving variants and diverse intervention strategies, traditional epidemiological models face limitations, making machine learning an attractive alternative for comprehensive modelling and prediction.

II. LITRATURE SURVEY

The study (reference [1]) is dedicated to enhancing the predictive capabilities of existing models concerning the spread of COVID-19 in the top five worst-hit countries: Brazil, India, Peru, Russia, and the USA. Researchers propose a novel approach known as the wavelet-coupled RVFL (WCRVFL) model, which integrates the random vector functional link (RVFL) network with 1-D discrete wavelet transform. Evaluation of the WCRVFL model is conducted against both the support vector regression (SVR) model and the conventional RVFL model. Empirical findings underscore the promising potential of the WCRVFL model in accurately forecasting COVID-19 spread up to 60 days in advance. Nevertheless, it is essential to acknowledge the limitations inherent in this study, including constraints related to data availability and accuracy, as well as the dynamic nature of the pandemic situation.

The study (reference [2]) examines time series data pertaining to COVID-19 cases in the top five affected countries: the US, Brazil, India, Russia, and Spain. Utilizing the ARIMA model, the study endeavours to forecast the future trajectory of virus spread. The forecast indicates that Russia and Spain have reached an inflection point, while the US, Brazil, and India continue to experience exponential growth. By July 31st, India and Brazil are projected to accumulate 1.38 million and 2.47 million cases, respectively, while the US is expected to report 4.29 million cases. However, it is imperative to acknowledge limitation inherent in the analysis, The accuracy of the forecast hinges heavily on the quality and reliability of the underlying data. The study (referenced [3]) employed a straightforward mathematical model and utilized a restricted set of epidemiological data to forecast the 2019-nCoV outbreak in China. Predictions from the model suggested a potential range of cumulative cases spanning from 76,000 to 230,000, with an anticipated peak of unrecovered infectives projected between 22,000 and 74,000 from late February to early March. After this peak, a swift decline in case numbers was anticipated until the outbreak subsided, expectedly occurring between early May and late June. It is imperative to acknowledge the limitations of this study, as the predictions rely on a simplistic model and a constrained dataset, potentially impacting the accuracy of the projections.

III. SYSTEM ARCHITECTURE

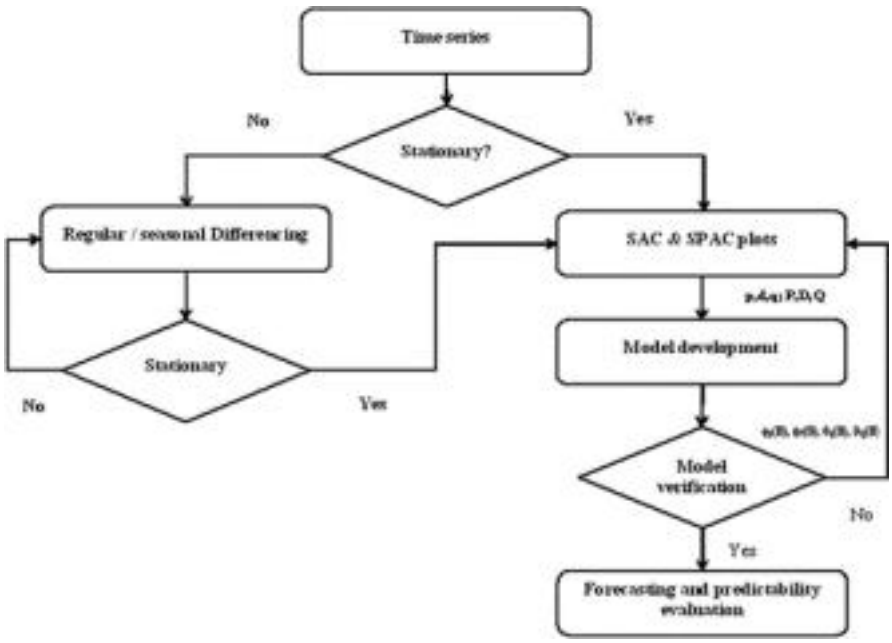


Fig 1: System Architecture

IV. SYSTEM MODULES

The project's development may entail numerous interconnected modules to ensure the establishment of a comprehensive and efficient system. Below are potential modules for consideration:

1. Data Collection and Preprocessing:

This module involves collecting diverse and reliable datasets related to COVID-19, encompassing infection rates, demographic information, testing data, and geographical details. Subsequently, the collected data is preprocessed to handle missing values, outliers, and standardize formats for consistency.

2. Exploratory Data Analysis (EDA):

Within this module, exploratory data analysis is conducted to discern trends, correlations, and patterns in the COVID-19 data. Visualization techniques, including charts and graphs, are employed to gain insights into the dynamics of virus spread.

3. Feature Engineering:

This module focuses on selecting and engineering pertinent features that can enhance the model's accuracy and effectiveness.

4. Machine Learning Model Development:

The development of a predictive model is carried out using machine learning algorithms such as regression, time series analysis, or deep learning. The model is trained on historical data to discern patterns and relationships.

5. Validation and Evaluation:

In this module, the dataset is split into training and testing sets to validate the model's performance. The model's accuracy, precision, recall, and other relevant metrics are evaluated to ensure its reliability. Integration of these modules enables the project to provide a comprehensive solution for tracking and forecasting the dynamic propagation of COVID-19.

V. SYSTEM IMPLEMENTATION

The implementation of the ARIMA (Auto Regressive Integrated Moving Average) model, a widely used time series forecasting method, involves several key steps:

1. Data Understanding:

Begin by thoroughly analyzing and understanding the time series data, including identifying trends, seasonality, and any other patterns that may influence the data.

2. Stationary Check:

Ensure that the time series data exhibits stationary, where its statistical properties remain constant over time. Stationary is essential for ARIMA models. If the data lacks stationary, apply differencing to achieve it by subtracting the previous observation from the current one.

3. Order of Differencing (d):

Determine the order of differencing (d) required to achieve stationary. This represents the number of times differencing is performed, with a value of 0 indicating stationary data.

4. Autocorrelation and Partial Autocorrelation Analysis:

Examine the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to identify suitable values for the autoregressive (AR) and moving average (MA) parameters. The ACF plot aids in determining the MA order, while the PACF plot assists in determining the AR order.

5. Identification of AR and MA Orders (p, q):

Based on the ACF and PACF plots, determine the appropriate orders for the AR (p) and MA (q) components of the ARIMA model.

6. Model Fitting:

Fit the ARIMA model to the training data using the determined values of p, d, and q. This involves estimating the coefficients of the AR and MA terms and finding optimal values.

7. Model Evaluation:

Evaluate the performance of the model on the validation or test dataset using suitable metrics such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE). Adjust the model parameters as needed to enhance performance.

8. Forecasting:

Utilize the trained and validated model to generate future predictions on new, unseen data. Create forecast intervals and visualize predicted values against actual values.

9. Model Refinement (if necessary):

Fine-tune the model based on its forecasting performance, adjusting orders (p, d, q) or considering additional factors influencing the time series.

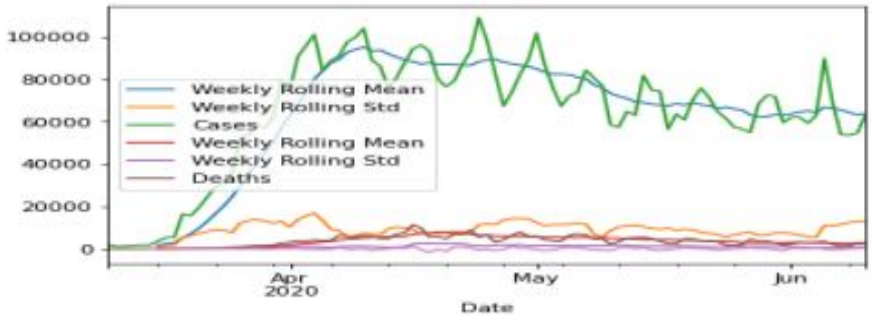
10. Final Model Deployment:

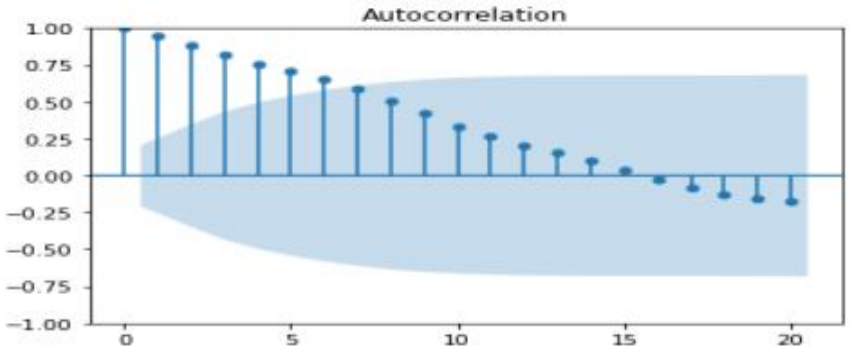
Deploy the refined ARIMA model for real-world predictions, facilitating practical applications in forecasting future trends.

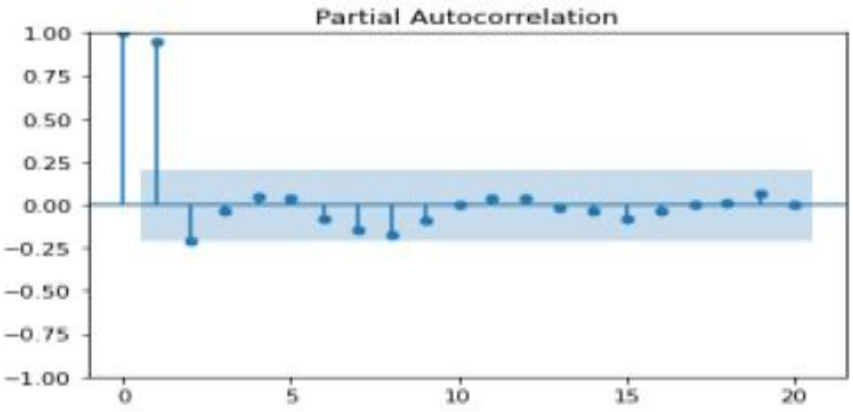
VII. SCOPE OF FUTURE APPLICATION

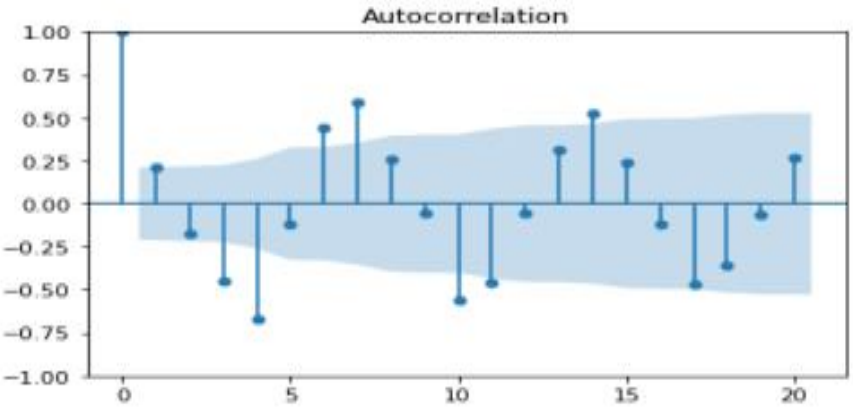
The scope of future application for this model encompasses a wide array of domains within the purview of public health and epidemiology. It offers the potential for real-time monitoring and forecasting of COVID-19 spread patterns, facilitating timely and targeted interventions aimed at curbing transmission rates and mitigating the impact of the pandemic. Through sophisticated data analytics and predictive capabilities, the model can inform decision-making processes at local, national, and global levels, enabling policymakers to allocate resources effectively and implement evidence-based public health measures. Moreover, the adaptable framework of the model enables its seamless integration into existing public health systems, fostering collaboration and coordination among stakeholders involved in pandemic response efforts. By harnessing advanced machine learning techniques and leveraging comprehensive datasets, it has the capacity to enhance situational awareness and provide invaluable insights into epidemiological trends and dynamics. This, in turn, empowers authorities to proactively address emerging challenges and adapt strategies in accordance with evolving circumstances. Looking ahead, the model's versatility extends beyond its application in addressing the COVID-19 pandemic. Its robust methodology and predictive capabilities render it applicable to other infectious diseases, offering a valuable tool for pre-emptive surveillance and response planning. Furthermore, the insights garnered from its implementation can contribute to the development of evidence-based policies and interventions aimed at safeguarding public health against future health threats. In essence, the model represents a significant advancement in epidemiological research and public health practice, poised to play a pivotal role in shaping the trajectory of pandemic management and preparedness efforts. As the global community continues to navigate the complexities of infectious disease outbreaks, the adoption and refinement of such innovative approaches hold promise for enhancing our collective resilience and capacity to respond effectively to emerging health challenges.

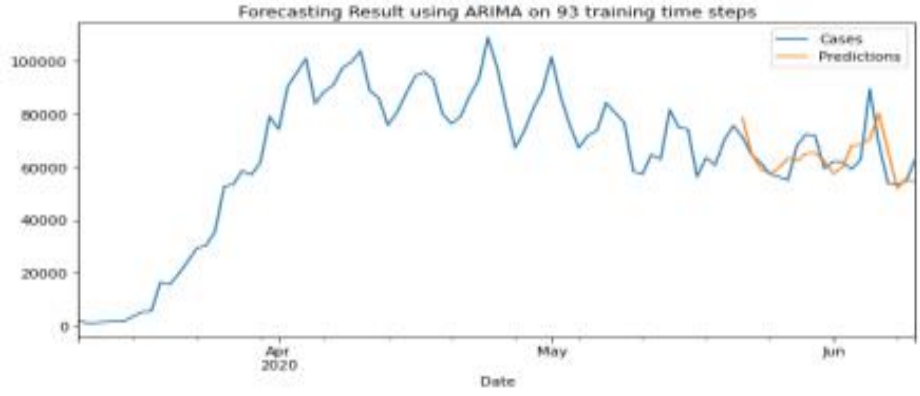
VIII. RESULTS











IX. CONCLUSION

In summary, the presented work constitutes a notable advancement in our collective endeavors to combat the COVID-19 pandemic and enhance readiness for future health crises. Leveraging advanced machine learning techniques, extensive datasets, and real-time data updates, the model addresses critical challenges posed by the pandemic. Amidst uncertain and swiftly evolving circumstances, this work underscores our capacity to utilize technology, data, and collaboration to confront global challenges. It offers a beacon of hope amidst the crisis, furnishing a more informed and efficient approach to pandemic management and preparedness for an uncertain future. As the battle against COVID-19 progresses, steadfast dedication to innovative, data-driven solutions remains paramount to safeguarding the health and well-being of individuals and communities worldwide. The development and deployment of this model signify a significant stride forward in this ongoing endeavour.

REFERENCES

[1]. B.B. Hazarika and D. Gupta, "Modelling and forecasting of COVID-19 spread using wavelet-coupled random vector functional link networks," Appl. Soft Comput., vol. 96, Nov. 2020, Art. no. 106626.
[2]. A.K. Sahai, N. Rath, V. Sood, and M. P. Singh, "ARIMA modelling & forecasting of COVID-19 in top five affected countries," Diabetes Metab. Syndr.: Clin. Res. Rev., vol. 14, no. 5, pp. 1419–1427, Sep. 2020.
[3]. L.Zhong, L. Mu, J. Li, J. Wang, Z. Yin, and D. Liu, "Early prediction of the 2019 novel Coronavirus outbreak in the mainland China based on simple mathematical model," IEEE Access, vol. 8, no. 1, pp. 51761–51769, 2020
[4]. Q.Lin et al., "A conceptual model for the Coronavirus disease 2019 (COVID-19) outbreak in wuhan china with individual reaction and governmental action", Int. J. Infect. Dis., vol. 93, no. 1, pp. 211-216, Apr. 2020.
[5]. N.Chintalapudi, G. Battineni and F. Amenta, "COVID-19 virus outbreak forecasting of registered and recovered cases after sixty day lockdown in italy: A. data driven model approach", J. Microbiol., vol. 53, no. 3, pp. 396-403,Jun. 2020.
[6]. D.H. Kim, M. W. Kim, B. J. Lee, K. T. Kim, and H Y Youn, "Data Flow Prediction Scheme using ARIMA Model," Proceedings of the 2018 Korean Society for Computer and Information Sciences Summer Conference, vol. 26, no. 2, pp. 141-142, 2018.
[7]. S.Siami-Namini, N. Tavakoli, and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 1394-1401, Dec. 2018.
[8]. S.Siami-Namini, N. Tavakoli, and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 1394-1401, Dec. 2018.
[9]. WangY-w, Shen Z-z, Jiang Y. Comparison of ARIMA and GM (1, 1) models for prediction of hepatitis B inChina. PloS one. 2018.
[10]. Fattah J, Ezzine L, Aman Z, El Moussami H, Lachhab A. Forecasting of demand using ARIMAmodel. International Journal of Engineering Business Management. 2018.