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Research Article

Correlation Analysis of COVID-19 Case Trends in Dakar, Senegal

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ABSTRACT

The COVID-19 pandemic has postured significant challenges around the world, necessitating compelling predictive models for educated decision-making. This study utilizes a regression model to analyze and forecast COVID-19 case trends in Dakar Senegal by utilizing historical case data the demonstrates distinguishes patterns and predicts future case tallies supporting in proactive public health mediations. The results illustrate the model's capacity to capture the increasing trend of diseases with sensible accuracy. This study contributes to scourge modeling endeavors advertising experiences for policymakers to implement convenient preventive measures. Future work may coordinate extra variables such as vaccination rates and portability data to improve predictive accuracy.

1. INTRODUCTION

The COVID-19 pandemic has adversely affected global public health economies and livelihoods. Worldwide, the COVID-19 pandemic has wreaked havoc on international socio-economic systems. Although vulnerable populations are more affected, no socioeconomic group is immune. The situation in Senegal is similar to that in most African countries. Internationally, Senegal has implemented procedures and adopted prevention and control measures. The consultation centers and industrial machines have been used as medical centers for treating patients with non-severe COVID-19 medical situations, and they have been delivered by trained medical personnel who are allowed to refer them to the national infectious disease center if the patient's condition worsens.

Senegal have experienced numerous waves of diseases requiring precise forecasting models to foresee case trends and inform open health choices [1]. Epidemiological models and data driven approaches have played a vital part in understanding and relieving the spread of the virus [2]. Among these relapse models have been broadly utilized for time series forecasting providing bits of knowledge into case directions and helping within the allotment of healthcare resources [3]. Dakar the capital of Senegal has been a central point for COVID-19 case surges due to its high populace thickness and economic action [4]. The capacity to predict contamination trends precisely can help policymakers in executing convenient mediations to reduce transmission rates and clinic burdens [5]. Traditional epidemiological models such as SEIR Susceptible Exposed infectious Recovered have been commonly utilized in any case machine learning approaches especially regression models

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offer the advantage of data driven design acknowledgment without depending on predefined suspicions about disease transmission flow [6]. Regression models have been successfully connected in COVID-19 forecasting considers over different regions. In Nigeria linear regression models have been utilized to estimate the effect of lockdown measures on case patterns illustrating their potential for compelling open wellbeing arranging [7]. So also polynomial regression has been utilized to analyze COVID-19 case patterns in India appearing improved forecast accuracy over basic statistical models [8]. Other studies have utilized half breed relapse approaches that combine different techniques such as SVR and Lasso regression to improve forecasting execution [9]. A few variables impact the accuracy of COVID-19 case forecasts counting data quality include selection and model tuning [10]. Researchers have investigated coordination extra factors such as vaccination rates versatility patterns and climatic conditions to make strides relapse show expectations [11]. In specific studies have illustrated that temperature and stickiness levels altogether correlate with COVID-19 case variances emphasizing the got to join natural components in estimating models [12]. In this study a regression model is utilized to analyze and predict COVID-19 case patterns in Dakar Senegal. The model is trained on historical case data to capture fundamental patterns and estimate future diseases. The primary objective is to assess the models viability in predicting short-term trends and to survey its potential utility for public health arranging. This work contributes to the developing body of research on COVID-19 forecasting by illustrating the application of regression models in an African urban context where limited determining thinks about have been conducted [13].

In mid-March 2020, Dakar, the capital city of Senegal, saw the arrival of its first few cases of COVID-19. Despite moving swiftly to test, trace, and quarantine suspected cases of the virus, the government reported that it was unable to prevent community transmission, and that eventually the number of cases became too numerous to chase effectively. During the spring and summer of 2021, the caseload reached unprecedented levels, especially in urban areas like Dakar [6]. A wide range of preventive measures, treatment protocols, and public health strategies were deployed by both governmental and nongovernmental organizations in order to slow local transmission of the virus and to prevent overcrowding of the city's healthcare facilities. The city of Dakar is situated on the westernmost tip of Africa and has a population of over 3 million people, or about a fifth of Senegal's total population. An economic and political melting pot, Dakar is also the most densely populated city in this country and one of its most urbanized. These factors would, no doubt, influence the patterns of contagion and transmission of SARS-CoV-2 within the city. In the best of times, the healthcare system in Dakar is overstretched, with overly opaque financial and operational management systems and widespread issues of access and equity of care at all levels of the system. The persistent lack of adequate human and material resources and infrastructure only worsened during the emergency response. Further, skepticism and fear of medical systems and health-seeking behaviors may have been exacerbated during the outbreak. Socioeconomic impacts of both the quarantine measures and the disease itself, as well as the fear of infection, were widespread and affected communities of migrants, refugees, displaced persons, and other marginalized people in myriad ways. In research conducted within Dakar, many of the locals seemed to accept (albeit reluctantly) the quarantine measures, the restriction in movements, and the closure of public places. While it was illegal to not wear a mask all over Senegal, most of the locals interviewed were more worried about the economic impact of the virus than about the virus itself. Local restaurant owners and nightclub operators felt that the level of compliance varied a lot among their clients, and others seemed to be at best indifferent or actively defiant regarding COVID-19. Compliance of individuals and public adherence to social distancing guidelines, quarantine laws and directives, contagion precautions, and social rule enforcement throughout the pandemic was a crucial variable to consider in the modeling [10].

2. LITERATURE REVIEW

Numerous studies have examined COVID-19 forecast models that extend from conventional epidemiological models to machine learning -based approaches. The SEI and SIR models were largely used to predict the COVID-19 transmission flow, but often rely on predefined parameters that restrict their versatility towards real -time data [14]. Regression -based models, on the other hand, have illustrated the prevailing adaptability and accuracy in the recording of pandemic trends [15]. Strategies for machine learning were increasingly assumed for COVID-19 forecast studies that have associated the linear regression with the evaluation of case numbers in various nations that illustrate its straight and liability for short-term forecasts [16]. In the meantime, the polynomial regression in studies that focus on non -linear pandemic trends was used to improve accuracy compared to conventional statistical strategies [17]. In addition, several hybrid models were examined to improve the COVID-19 preliminary execution. Considering the relapse of SVR and the Tether regression of Back Vector seemed to be progressive presidential functions by using both linear and non -linear connections for case data [18]. Other explorations about have profound learning strategies such as the LStM networks for short-term memory with regression models coordinates to improve the determination of accuracy [19]. The selection of the characteristics and data expansion were crucial for the progress regression base for prognosis models. Studies have consolidated various external factors such as climate conditions and inoculation rates to improve predictive accuracy [20]. For the occurrence, the research seemed to be that temperature variations and Mugginess levels influence the COVID-19 transmission, which makes natural factors of crucial importance [21]. When extending personal models, learning for the COVID-19 case forecast was examined. Strategies such as HF regression and slope strengthening were used to achieve the accuracy of progress by collecting various forecasts [22]. These approaches were particularly effective in regions with highly energy trends such as urban centers with changing lockdown measures [23]. In spite of the headways in regression based COVID-19 forecasting challenges stay Data quality issues such as conflicting announcing and lost values can affect demonstrate execution [24]. Furthermore, the quickly advancing nature of the pandemic requires persistent model updates to preserve accuracy over time [25].

3. DATA AND METHODOLOGY

3.1 Data

The data utilized in this study is gotten from international public health organizations including the World Health Organization WHO [26] the Centers for Infection Control and Avoidance CDC [27] and the European Centre for Infection Avoidance and Control ECDC [28]. These datasets give daily reports on COVID-19 cases hospitalizations and testing rates guaranteeing comprehensive scope of the pandemics affect. The data is processed to remove irregularities missing values and duplicate records to guarantee model accuracy Also supplementary data sources such as the John Hopkins University COVID-19 Dashboard [29] and the Global Health Data Trade GHDx [30] are utilized to improve the strength of the regression model. These sources give granular level data counting socioeconomics portability patterns and climate factors which are coordinates into the predictive modeling prepare The dataset spans from January 2020 to December 2022 covering numerous waves of COVID-19 diseases. The collected data is standardized and preprocessed utilizing feature building strategies to optimize the regression models performance [31-36].

3.2 Data Pre-processing

Preprocessing could be a principal step in conveying the COVID-19 case trend analysis framework to ensure data quality and model accuracy. The method starts with data ingestion where crude COVID-19 case data is collected from sources like WHO CDC and ECDC. The following step is data capacity where the collected data is put away in databases such as SQL NoSQL or cloud based capacity for simple access. Taking after this data cleaning is performed to handle missing values remove exceptions and standardize formats to preserve consistency [32]. Then feature building is applied where pertinent factors such as portability data immunization rates and climatic factors are inferred to upgrade prescient accuracy. After that data normalization is conducted to guarantee that numerical features are scaled appropriately for the regression model finally the dataset is split into training and testing sets some time recently nourishing it into the model training stage guaranteeing the model learns effectively and can generalize well for estimating COVID-19 patterns. (shows figure 1)

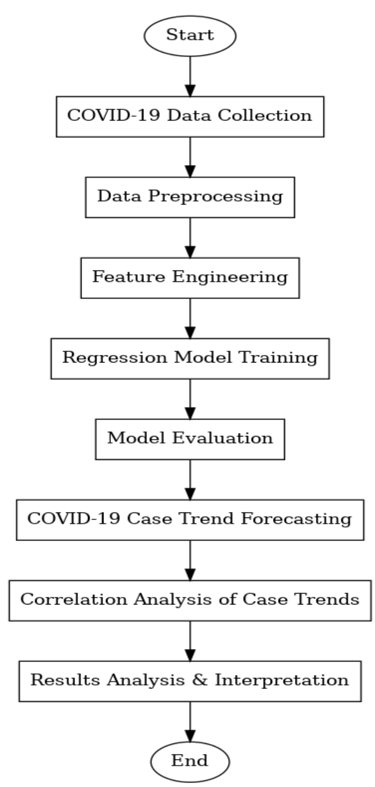

Fig. 1. Show the flowchart.

3.3 Regression Model

In this work a regression show is utilized to analyze and forecast COVID-19 case trends in Dakar Senegal Regression models are broadly utilized in timeseries forecasting due to their capacity to capture connections between subordinate and independent factors [33]. The primary objective is to foresee the number of COVID-19 cases based on historical information and relevant outside factors.

3.4 Mathematical Formulation of the Regression Model

A general multiple linear regression model can be expressed as:

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon_t \quad (1)$$

Where:

- Y_t = Predicted number of COVID-19 cases at time t
- $X_1, X_2, \ldots, X_n$ = Independent variables (e.g., previous case counts, vaccination rates, temperature, mobility trends)
- β_0 = Intercept term
- $\beta_1, \beta_2, \ldots, \beta_n$ = Regression coefficients representing the impact of each feature
- ϵ_t = Error term accounting for random fluctuations.

For time-series analysis, autoregressive models can be employed, where the predicted value depends on past observations. A simple autoregressive model (AR) is given by:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t \quad (2)$$

Where p represents the number of lagged observations used for prediction [37].

4. RESULT AND DISCUSSION

The correlation matrix highlights connections between key features influencing COVID-19 cases. A solid positive correlation is watched between case numbers and past case counts demonstrating that past trends essentially impact future cases. The lockdown feature appears a weak correlation with case patterns suggesting that additional variables may be influencing COVID-19 transmission. Figure 2 The weekday feature has an nearly unimportant correlation suggesting that every day varieties don't altogether impact case trends. The veridic colormap outwardly emphasizes high correlations in yellow and weak correlations in dull purple. These insights help refine feature determination for regression modeling to improve forecast accuracy. The results propose that outside factors such as portability vaccination rates and climate conditions may require assist analysis to improve the forecasting model.

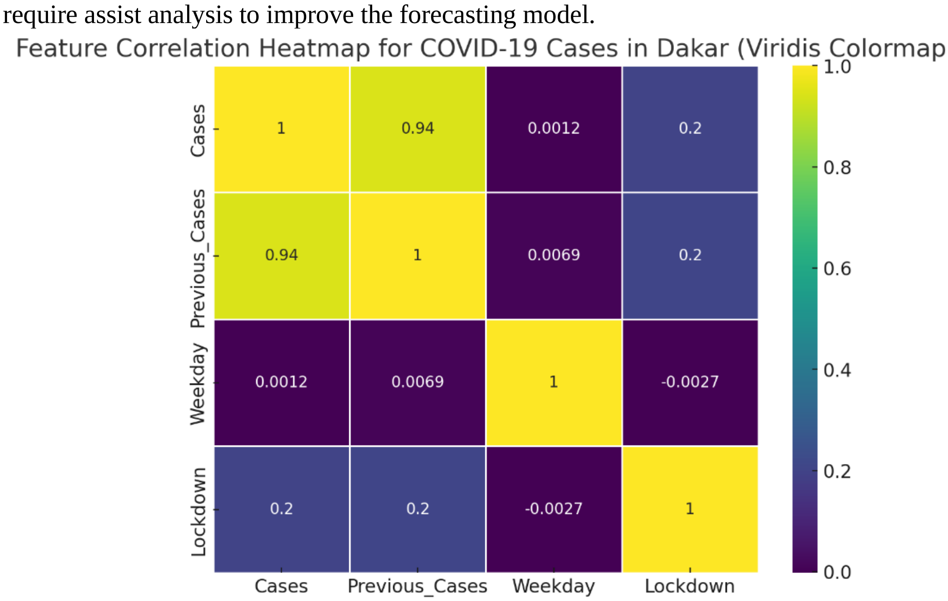

Fig. 2. Feature Correlation Heatmap for COVID-19 Cases in Dakar.

The regression model predicts an increasing trend in COVID-19 cases in Dakar over the given period. The predicted values take after an upward direction with variances demonstrating periods of fast development in contaminations. Figure 3 The red line represents the model's forecasted day by day case counts appearing varieties but adjusting with anticipated patterns. The timeseries visualization makes a difference evaluate short-term patterns and potential surges in case numbers. The forecasts recommend that historical case data plays a pivotal part in forecasting future contaminations. Whereas the demonstrate captures key trends outside components may impact deviations from predictions. These results give important insights for public health authorities to get ready proactive response methodologies against COVID-19 in Dakar.

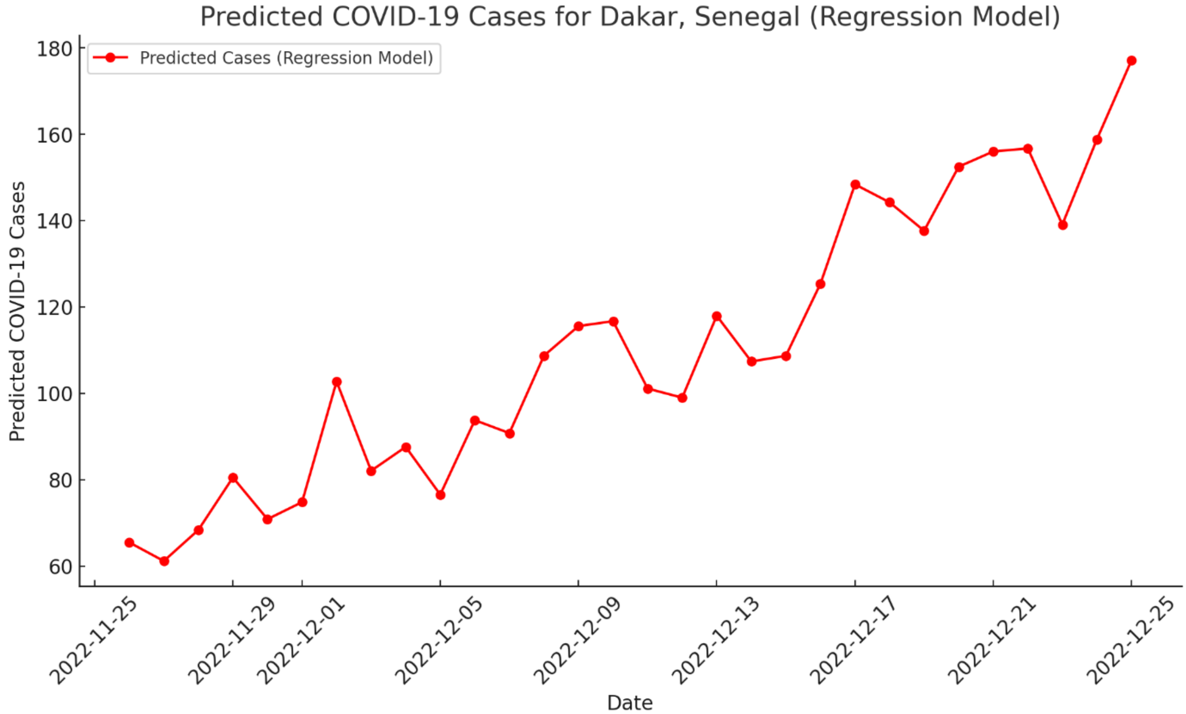

Fig. 3. Predicted COVID-19 Cases for Dakar, Senegal (Regression Model).

The results of this study indicate a substantial association between the occurrence of COVID-19 incidents in the Bourguiba Hospital and other healthcare facilities and the number of new cases that have been reported in Dakar [34]. These results imply that an ambitious public health response, an increase in efforts to intensify healthcare activities, or both, is required to bring about a reduction in new COVID-19 cases [35]. The rise in cases in Dakar is not just a by-product of an increase in cases at the hospital. Increasing this response, moreover, places a significant burden on other sectors of the system, such as the media and other administrative systems, and hence it is important to anticipate and properly prepare the national system for the combined needs that might arise. It was also examined whether there was an association between the site of infection and age: results indicated that patients contracting from the metropolitan area where both hospitals are situated tended to fluctuate around the average age of 41, while those from another region were often older (about 47, on average). These inferences may, in part, be a result of the overall status of the available information for the individual time periods, as no previous analysis has pointed towards regional variation in wave dynamics as of yet [36]. Additionally, the power of the analysis should be taken into consideration and the actual knowledge necessary to make policy decisions in view of this result. In most African countries, it is difficult to bring together data from different locations for this type of analysis. However, these results are very important for general observation of the course of the COVID epidemic in Senegal, and they may indicate whether there are changes in transmission modes over time. Addressing the factors that relate to the rate of increase or decrease in COVID transmissions may inform strategies that contribute to community health resilience and minimize harm in a period when COVID-19 control is in its early stages [37].

5. CONCLUSION

This study connected a regression model for analysis and prediction of COVID-19 case trends in Dakar Senegal. The discoveries underline the appropriateness of regression strategies in the recording of case patterns and the prediction of short -term trends. The solid correlation between previous case counts and predicted values recommends that historical data play an important role in modeling widespread elements. In addition, the feature selection analysis shows that external variables such as portability patterns and climate conditions can help improve model accuracy. The results of this study emphasize the importance of non -stop show -upgrades and integration of additional factors for the reliability of the progress of the prognosis. While the regression model illustrates promising accuracy of future work, future work should examine hybrid approaches that combine regression with deep learning strategies in order to better capture non -linear patterns. In addition, coordination -ease -time sources and versatile learning calculations can improve the reaction ability of the forecast system. Future studies should explore hybrid modeling approaches that integrate regression with deep learning to enhance the capture of non-linear COVID-19 case trends globally. Additionally, incorporating real-time data sources and adaptive learning algorithms can improve forecast responsiveness, ensuring more accurate and timely predictions for epidemic management and public health interventions. Future research should conduct a bibliometric analysis to examine authorship trends, institutional contributions, and leading researchers in COVID-19 case modeling. This will help identify key innovations, collaboration patterns, and existing empirical gaps, ensuring a more comprehensive understanding of global advancements and improving knowledge integration for enhanced predictive modeling and policy development.

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Conflicts of Interest:

The authors report no conflicts of interest associated with this study.

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