CMJ. 2025;47(4):32-39.
DOI: 10.7197/cmj.1807704

Cumhuriyet Medical Journal

| cmj.cumhuriyet.edu.tr | Founded: 2004 Available online, ISSN:1305-0028 Publisher: Sivas Cumhuriyet Üniversitesi

Investigation of Covid 19 Cases in Sivas Province with Time Series Analysis

Esra Akaydın Gulturk[1,a,*], Emek Guldogan [2,b]

[1] *Department of Biostatistics, Faculty of Medicine, Sivas Cumhuriyet University, Sivas, Türkiye*
[2] *Department of Biostatistics and Medical Informatics, Faculty of Medicine, Inonu University, Malatya, Türkiye*
**Corresponding author*

Research Article

History

Received: 20/10/2025
Accepted: 22/12/2025

Copyright

This work is licensed under Creative Commons Attribution 4.0 International License

ABSTRACT

Objective: This study aims to compare the predictive performance of classical statistical, machine learning, and deep learning-based modeling approaches by analyzing the monthly COVID-19 case numbers in Sivas province. The goal is to identify the most suitable model capable of accurately forecasting the future progression of the pandemic.
Method: Confirmed COVID-19 case data for March 2020 -August 2022, were obtained from the Sivas Provincial Health Directorate. The stationarity of the series was evaluated using the Augmented Dickey Fuller (ADF) and KPSS tests. A logarithmic transformation was applied to reduce variance imbalance. The data were split into training (70%), validation (10%), and test (%20) sets. Classical SARIMAX, machine learning based Prophet, and deep learning-based LSTM models were employed. Model performance was compared using RMSE and SMAPE.
Results: The LSTM model achieved the lowest error values (RMSE = 1.975; SMAPE = 109.9%) and demonstrated the highest prediction accuracy among all models. The logarithmically transformed SARIMAX model ranked second (RMSE = 2.093; SMAPE = 114.3%), while the Prophet model ranked third (RMSE = 5.290; SMAPE = 116.6%). In contrast, models trained on raw (untransformed) data exhibited significantly higher error levels, demonstrating poor forecasting performance.
Conclusion: Although logarithmic transformation improved the performance of the classical models, the LSTM model provided the highest accuracy for complex and nonlinear time series such as COVID-19. These findings demonstrate that deep learning approaches serve as powerful alternatives for epidemiological forecasting and may significantly support local health planning and resource allocation.

***Keywords*:** *COVID-19, Time Series Analysis, SARIMAX, Prophet, LSTM*

Sivas İlinde Covid 19 Vakalarının Zaman Serileri Analizi İle İncelenmesi

Araştırma Makalesi

Süreç

Geliş: 20/10/2025
Kabul: 22/12/2025

Telif Hakkı

Bu Çalışma Creative Commons Atıf 4.0 Uluslararası Lisansı Kapsamında Lisanslanmıştır.

ÖZ

Amaç: Bu çalışma, Sivas ilindeki aylık COVID-19 vaka sayılarını analiz ederek klasik istatistiksel, makine öğrenimi ve derin öğrenme tabanlı modelleme yaklaşımlarının tahmin performansını karşılaştırmayı amaçlamaktadır. Hedef, pandeminin gelecekteki seyrini doğru bir şekilde tahmin edebilecek en uygun modeli belirlemektir.
Yöntem: Mart 2020- Ağustos 2022 tarihleri arasında teyit edilmiş COVID-19 vaka verileri Sivas İl Sağlık Müdürlüğü'nden temin edilmiştir. Serinin durağanlığı Augmented Dickey–Fuller (ADF) ve KPSS testleri kullanılarak değerlendirilmiştir. Varyans dengesizliğini azaltmak için logaritmik dönüşüm uygulanmıştır. Veriler eğitim (%70), doğrulama (%10) ve test (%20) setlerine ayrılmıştır. Klasik SARIMAX, makine öğrenimi tabanlı Prophet ve derin öğrenme tabanlı LSTM modelleri kullanılmıştır. Model performansı RMSE ve SMAPE kullanılarak karşılaştırılmıştır.
Bulgular: LSTM modeli en düşük hata değerlerini elde etti (RMSE = 1,975; SMAPE = %109,9) ve tüm modeller arasında en yüksek tahmin doğruluğunu gösterdi. Logaritmik dönüştürülmüş SARIMAX modeli ikinci sırada (RMSE = 2,093; SMAPE = %114,3), Prophet model ise üçüncü sırada (RMSE = 5,290; SMAPE = %116,6) yer aldı. Buna karşılık, ham (dönüştürülmemiş) verilerle eğitilen modeller, önemli ölçüde daha yüksek hata seviyeleri göstererek zayıf tahmin performansı sergiledi.
Sonuç: Logaritmik dönüşüm klasik modellerin performansını iyileştirmiş olsa da LSTM modeli COVID-19 gibi karmaşık ve doğrusal olmayan zaman serileri için en yüksek doğruluğu sağlamıştır. Bu bulgular, derin öğrenme yaklaşımlarının epidemiyolojik tahminler için güçlü alternatifler olduğunu ve yerel sağlık planlaması ve kaynak tahsisini önemli ölçüde destekleyebileceğini göstermektedir.

Anahtar kelimeler: COVID-19, Zaman Serisi Analizi, SARIMAX, Prophet, LSTM

[a] *esra0709.eg@gmail.com* *0000-0003-0978-3091*
[b] *emek.guldogan@inonu.edu.tr* *0000-0002-5436-8164*

How to Cite: Akaydın Gulturk E, Guldogan E. Investigation of Covid 19 Cases in Sivas Province with Time Series Analysis, Cumhuriyet Medical Journal. 2025;47(4):32-39.

Introduction

The COVID-19 pandemic began in Wuhan, China, in December 2019 and quickly spread across the globe, becoming a worldwide public health concern.[1] This situation to date has placed an unprecedented strain on health services.[2] Because the course of the pandemic varied greatly between countries and even cities, mathematics and statistics were used to simulate how outbreaks spread at the regional level.[3]

In Turkey, it is crucial to be able to predict the number of cases in the short and medium term, especially at the local level, to plan healthcare services, allocate resources, and take public health measures in a timely manner.[4] In this scenario, being able to accurately predict the number of COVID-19 cases is critical for putting logistics, supply chain management, hospital staffing and supply planning, and vaccination programs into action.[5] These kinds of forecasting models are crucial for public health and safety because they provide decision makers early warning systems to help slow the spread of illness.[6] Because of this worldwide health problem, many different computer approaches, such as machine learning and classical time series models, have been employed to estimate how COVID-19 would spread and what its effects will be. These forecasts have been very useful for public health work.[7,8] For instance, researchers have used models like ARIMA and exponential smoothing to anticipate COVID-19 cases in different nations. This case study shows how useful these kinds of models can be for understanding how a pandemic spread.[9] Hybrid models that combine classic statistical approaches with deep learning architecture like Long Short-Term Memory have been better at forecasting complicated epidemiological patterns, particularly for events that change quickly, like pandemics.[10]

Time series analysis is a sophisticated statistical tool that can make predictions about the future by modeling how different pieces of data relate to each other across time.[11] Epidemiology can benefit from examining the efficacy of diverse modeling techniques on rapidly fluctuating and seasonal datasets such as COVID-19.[12] When it comes to this, there are three primary ways to look at time series data: conventional statistical techniques, Machine Learning (ML)-based models, and Deep Learning (DL)-based. These models are known as Artificial Neural Network (ANN) models.[13]

It is necessary to compare different ML models to find out which one is better at forecasting how the epidemic will go.[14] ML algorithms are especially impressive since they can learn from current data and generate predictions about the future. In this situation, models like the Prophet model, which makes daily, weekly, and periodic predictions on time series data, may provide reliable predictions, particularly when the data is complicated as during a pandemic.[8] On the other hand, Linear Regression, Exponential Smoothing, and ARIMA are more classic time series models that are also often used to learn about how diseases spread and predict where they will spread next.[5,13]

Recent research has shown that DL models like gated recurrent units and long short-term memory are better at predicting COVID-19 than standard statistical approaches like ARIMA and SARIMA.[14] This demonstrates the superiority of DL methods, especially when dealing with complex and non-linear time series data.[10]

During the pandemic, creating accurate, reliable, and localized forecasting models is strategically essential. These models helped us understand epidemiological trends, manage the burden on the healthcare system, plan testing capacity, monitor hospital occupancy rates, and prepare for potential new waves.[15] Analyses conducted at the regional level, in particular, examine how national policies affect people on a small scale and provide evidence-based support to local health authorities for their decisions.[16] So, the goal of this research is to examine how well various time series forecasting models work and make more accurate predictions on how the COVID-19 pandemic will go in the future. The research seeks to enhance the selection of the most suitable model by assessing the efficacy of various models in epidemic forecasting, particularly via a comprehensive analysis of the distinctions among conventional statistical techniques, ML, and DL approaches.[17] Using ML-based hybrid methods gives more accurate and economical predictions, especially for complicated and nonlinear time series, since typical linear models don't work.[18] Different research have looked at how well different models, such Linear Regression, Exponential Smoothing, ARIMA, Prophet, Gated Recurrent Units, and Long Short-Term Memory, can predict COVID-19 instances in this situation.[5,8,19]

The objective of this research is to evaluate the efficacy of several time series modeling techniques, including traditional statistical, machine learning (ML), and deep learning (DL) methods, using monthly COVID-19 case data from Sivas province, in order to identify the method with the greatest predictive capability. The research uses the SARIMAX, Prophet, and LSTM models classical, machine learning, and deep learning models, respectively. This comparison gives health officials a scientific reason to build early warning systems by giving them better projections of how the disease will spread in their area.

The significance of the study lies in its elucidation of the strengths and drawbacks of various modeling methodologies in quickly evolving and unpredictable epidemiological contexts, exemplified by COVID-19. The results make it possible to create a modeling method that can be used in Sivas province and other areas with comparable demographic and epidemiological profiles. This work further adds to the body of research by combining the predictive potential of DL with epidemiological analysis while keeping the explainability of traditional statistical models.

Methods

Data Source

This study utilised the daily confirmed COVID-19 case numbers in Sivas Province between March 2020 and August 2022 The dataset comprised all verified case records reported during the study period and was obtained from the routinely maintained surveillance system of the Sivas Provincial Health Directorate. No missing data were identified. To visualise the general trend and seasonal fluctuations more clearly, the daily case numbers were aggregated into monthly totals. Ethical approval for the study was granted by the Sivas Cumhuriyet University Non-Interventional Clinical Research Ethics Committee on 23.06.2021 (approval number: 2021-06/42).

Data Preprocessing

In the modeling process, the dataset was divided into 70% training, 10% validation and 20% test subsets to enable independent evaluation of the prediction performance. In order to prevent scale differences from affecting the model results, all variables were transformed into 0-1 range by Min-Max normalization method.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Stationarity Analysis

To apply linear models correctly in time series analysis, the series must meet the stationarity assumption. So, the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are used to check whether the series is stationary. The ADF test is significant (p <0.05) and the KPSS test is not significant (p> 0.05), which means that the data is stationary. Stationarity denotes that a time series' statistical qualities stay the same over time. This is based on the idea that the model parameters stay the same throughout time.[20]

Models

SARIMAX Model

The SARIMAX model (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors) is one of the oldest time series models. It uses prior observations (AR), differencing (I), error terms (MA), and seasonal structures (S) to guess the series.[21] This approach can represent complicated patterns in time series data by combining seasonal and non-seasonal parts.[22] The SARIMA model is a popular time series model for predicting infectious diseases that does a good job of capturing trends and seasonal changes.[23] The model has both seasonal and non-seasonal parts, which are shown by the parameters (p, d, q) and (P, D, Q)s for the autoregressive, differencing (I), and moving average components.[23] In real life, the SARIMAX model, which is an upgraded version of the SARIMA model, may make better predictions by letting outside regressors be included.[24]

You may use ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) to figure out how the time series is related to its historical values. ACF indicates the general pattern of autocorrelation in the series, whereas PACF shows the direct influence of each lag on the series by getting rid of the effects of other variables in between.[25] We use these studies to figure out what the parameters p and q are in the SARIMAX model.

The SARIMAX model is a SARIMA model that has outside variables (X) and is written like this:

$$SARIMAX(p,d,q) \times (P,D,Q)_s \quad (2)$$

We use a multivariate linear regression equation to describe the instrumental variables:

$$y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \omega_t \quad (3)$$

Here;

β_0: Constant term,

$\beta_1, \beta_2, \ldots, \beta_k$: Regression coefficients of exogenous variables,

$X_{1,t}, \ldots, X_{k,t}$: Observations associated with the dependent variable y tile,

ω_t: is the stochastic error term.

The error term is expressed as follows:

$$\omega_t = \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D}\epsilon_t \quad (4)$$

Combining equations (3) and (4), the general form of the SARIMAX model is obtained:

$$y_t = \beta_0 + \sum_{i=1}^{k} \beta_i X_{i,t} + \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D}\epsilon_t \quad (5)$$

This model represents the dynamic structure of the series by combining past observations with seasonal and exogenous effects. Where:

p=0: No autoregressive term,

d=2: The series is differenced twice,

q=2: There are two lagged MA terms,

P=0, D=1, Q=1: Seasonal components,

s=12: Monthly seasonal cycle.

The Akaike Information Criterion (AIC) used in model selection is a measure that balances model complexity with goodness of fit and is calculated using the following formula:

$AIC = 2k - 2\ln(L)$, where k is the number of parameters in the model and L is the maximum likelihood value. The model with a lower AIC value is considered to fit the data better.

Prophet Model

Facebook's Prophet Model is a strong and flexible way to make predictions that looks at trend, seasonality, and error components in time series individually26. The general form of the model is as follows:

$$y_t = g_t + s_t + \epsilon_t$$

where gt is the trend part, st is the seasonal part, and ϵ_ is the random error.[26]

The Prophet Model works well even when there is missing data, trends change, or there are outliers. It works especially well with volatile series like COVID-19.[27] The model is designed with just two columns (ds: time, y: target variable), and predictions are produced using the Prophe object. In this research, the Prophet model includes a monthly seasonality component and uses log-transformed data. In the model's outputs, "yhat" indicates the expected values. Prophet further increases the model's explainability by visually separating the trend and seasonality components.

Deep Learning Model: LSTM

The Long Short-Term Memory (LSTM) model is a kind of artificial neural network that can learn long-term relationships in time series. The model outperforms traditional techniques, particularly in series with nonlinear and abrupt changes.[28]

To better capture the fluctuating rhythm of the COVID-19 time series, the LSTM model used in this study has two hidden layers. Each layer contains 32 neurons, and a 25% dropout is applied at the layer outputs to prevent overfitting. The time

delay (window size) was set to 12 months; thus, the model incorporated the subsequent year's epidemiological pattern into its memory fabric for each prediction. The training process consisted of 50 epochs with a batch size of 8, and the Adam optimizer with a learning rate of 0.001 was used. All variables were scaled to the 0–1 range using the Min–Max method before being fed into the model. This parametric approach enabled the LSTM architecture to represent the wave-like and irregular nature of the outbreak more consistently. The selection of LSTM hyperparameters, including the number of units, dropout rate, batch size, and epoch value, was guided by empirical optimization. These values fall within the commonly used ranges reported in the deep learning literature for small-to-medium-sized time-series datasets, ensuring a balance between model complexity, learning stability, and generalisability.

Model Performance Evaluation

The models' performance was evaluated using four basic error measures: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Symmetric Mean Absolute Percentage Error.

These criteria are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} |$$

$$SMAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{| y_i - \hat{y}_i |}{(| y_i | + | \hat{y}_i |)/2}$$

Compared to the standard MAPE comparison, SMAPE provides more reliable results for values close to zero.[29] If all RMSE, MAE, MAPE, and SMAPE values are low, the model makes very accurate predictions. When RMSE, MAE, MAPE, and SMAPE values are lower, the model makes more accurate predictions.

Model Selection and Robustness

In this study, Root Mean Square Error (RMSE) was used as the primary model evaluation criterion, while Symmetric Mean Absolute Percentage Error (SMAPE) was used as a secondary criterion. The optimal parameter combinations for SARIMAX models were first determined by considering Akaike Information Criterion (AIC) values; then validated by RMSE and SMAPE performance on the test set. The forecasting performance of the Prophet and LSTM models was also compared on the same test period. Model suitability was evaluated by examining the autocorrelation function (ACF) graphs of the residual series and the forecast–observation overlaps. The hyperparameters of the LSTM model (e.g., window length, number of neurons, epoch value) were optimized considering the early stopping method and validation loss criteria.

Statistical Methods

In this work, Python 3.11.9 was used to do time series analysis, statistical modeling, and DL-based forecasting. Data processing and analysis were performed using the libraries "pandas", "numpy", "statsmodels", "prophet", "scikit-learn", "tensorflow", "keras", "matplotlib", and "seaborn". NumPy version 1.26.4 was used to assure complete compatibility with the Prophet model. To make sure that the studies could be repeated, all models had a fixed random state (random_state=42).

Results

In the time series analysis of COVID-19 positive case numbers, the short-term forecasting performance of different modeling approaches was evaluated. In this context, the forecasting performance of the SARIMAX model, a classical statistical method, the machine learning-based Facebook Prophet algorithm, and the deep learning-based LSTM model were compared. Before modeling, the stationarity of the series was examined using the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. When the results of both tests were evaluated together, it was concluded that the time series used in the analysis met the stationarity condition.

A logarithmic transformation was applied to the data to reduce variance differences in the series, and this process was used to improve the prediction performance in both SARIMAX and Prophet models. Autocorrelation (ACF) and partial autocorrelation (PACF) graphs were examined to investigate the relationship of the time series with past values (Figure 1). Based on the ACF and PACF analyses, the appropriate orders for the ARIMA model were determined. According to the lowest Akaike Information Criterion (AIC) value, the SARIMAX (0, 2, 2) (0, 1, 1) $_{(12)}$ model was found to provide the best fit (AIC = 7174.37) (Table 1). The ADF test statistic was-3.832 with p = 0.0026 (p < 0.05); in the KPSS test, the test statistic was 0.398 and p = 0.078 (p > 0.05) (Table 2). These results indicate that the series is stationary.

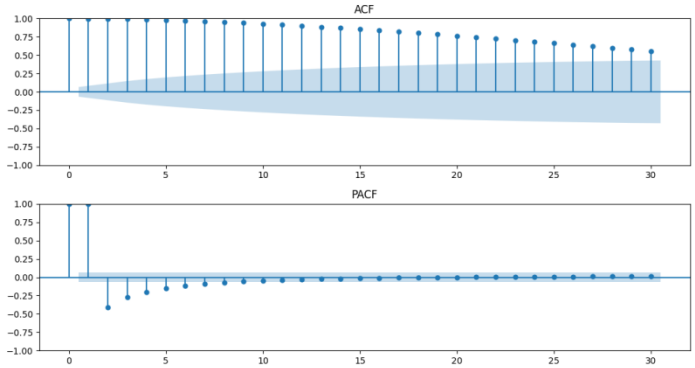


Figure 1. *ACF and PACF Graphs*

Tablo1. *Model Fit criteria comparison*

Model	(p, d, q)	(P, D, Q, s)	AIC
SARIMAX	(0, 2, 2)	(0, 1, 1, 12)	7174.37

Tablo 2. *Time series stationarity test results*

Test Name	Test Statistic	p value
ADF	-3.832	0.0026**
KPSS	0.398	0.078

Figure 2 shows the model's predicted performance on the test data for 2022. The prediction values (green line) are often consistent with the test data trend; the model accurately reflects the trend's direction.

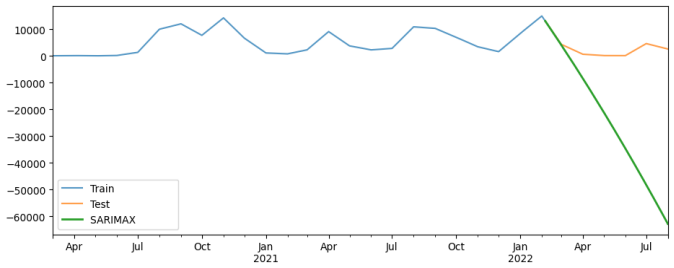


Figure 2. *SARIMAX Model Forecast Results for Training and Test Periods.*

The SARIMAX model in Figure 3 properly predicted the main trend direction in its 30-day forward projections; nevertheless, the forecast curve is less volatile than the real data's seasonal oscillations and spikes. This shows that the model can accurately predict the short-term direction.

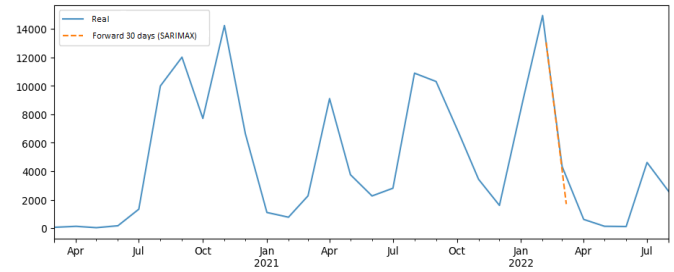


Figure 3. *30 Day Forecast Results of SARIMAX Model*

The SARIMAX model, following logarithmic transformation (Figure 4), accurately captured the overall trend and decreased the margin of error due to variance homogeneity. Log-transformation improved the model's predictive potential by decreasing variance instability. During the test period, the altered model had a much lower error rate (RMSE=2,093.50) than the conventional SARIMAX model.

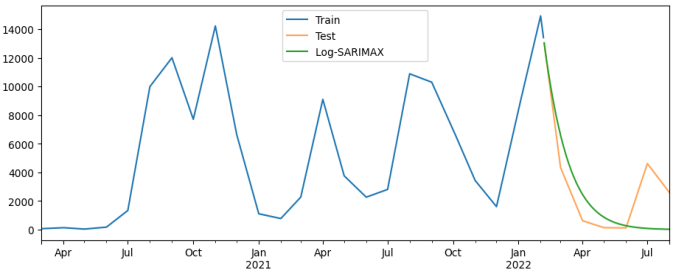


Figure 4. *Estimation Results for the Log-transformed SARIMAX Model*

Figure 5 illustrates the Prophet model's logarithmic predictions. It generally represents the pandemic's changing character. The darkened region shows the extent of expected uncertainty.

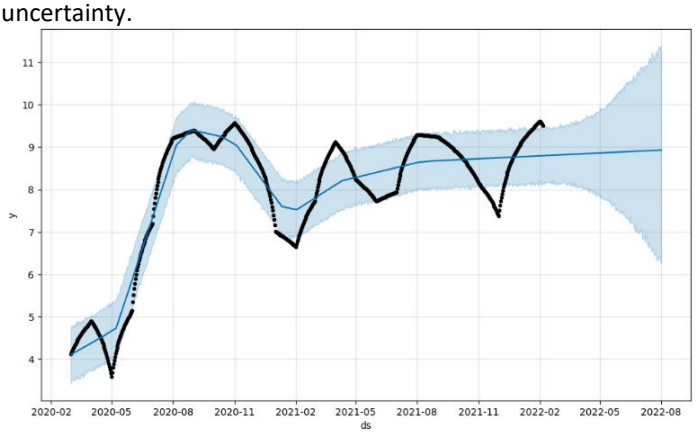


Figure 5. *Forecast Results for the Log-transformed Prophet Model*

Figure 6 depicts the series' long-term rising trend, while the graph depicts the repeated weekly pattern of case rises and reductions. Wednesday saw the greatest weekly rise in case numbers.

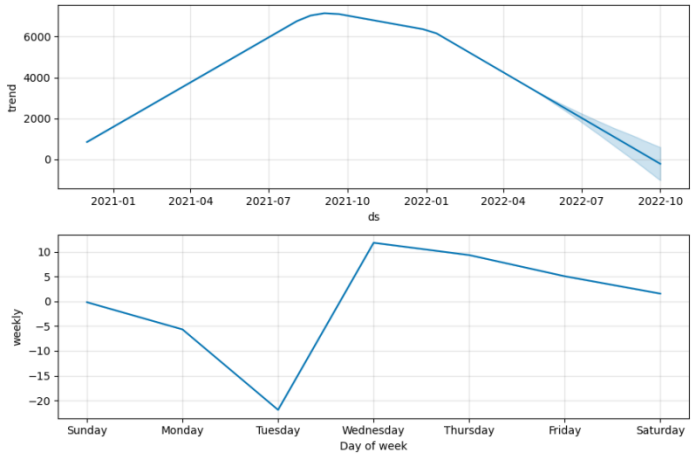


Figure 6. *Trend and Weekly Components of the Log-transformed Prophet Model*

The model's logarithmic estimates are rescaled to their original scale. The projections account for short-term changes while predicting a more steady trend in the long run.

When the logarithmic Prophet model's predictions are rescaled to their original size (Figure 7), the model accurately follows overall trends. Figure 8 depicts the Prophet model's prediction results using raw data, with the blue line representing the model predictions, the black dots representing the observed values, and the light blue shade representing the 95% confidence interval. The Prophet model dependably catches the trend but tends to smooth out short-term volatility.

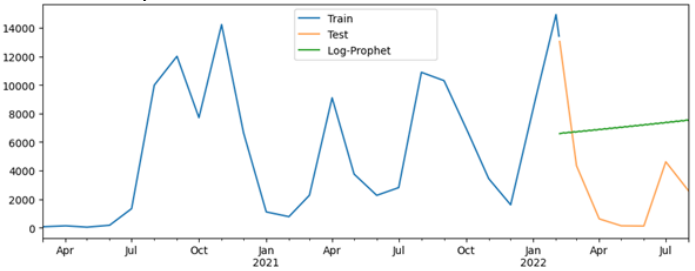


Figure 7. Log-transformed Prophet Model Estimation Results (Original Scale)

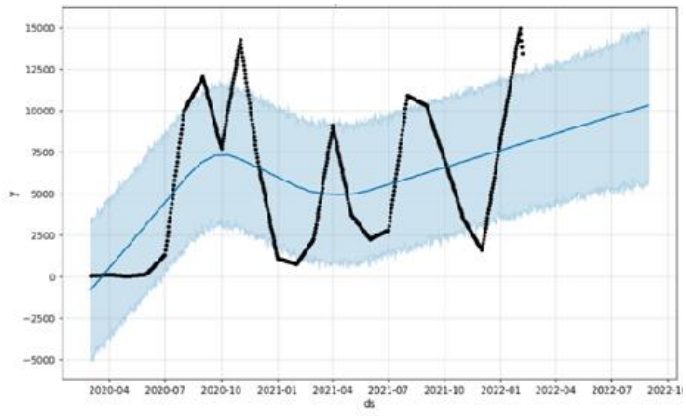


Figure 8. *Prediction Results of COVID-19 Positive Case Numbers with Prophet Model*

Figure 9 shows how the model's trend and seasonality parts break down. We utilized the Prophet model, which is a machine learning-based technique, to look at the time series of COVID-19 positive case counts. The Prophet model anticipates the time series using trend, seasonality, and residual components. The model's predicted time series components are given in separate panels. The top panel includes the series' overall composition (trend + seasonality + residual), the second panel contains the trend component, the third panel contains the seasonal component, and the bottom panel contains the residual component (Figure 10).

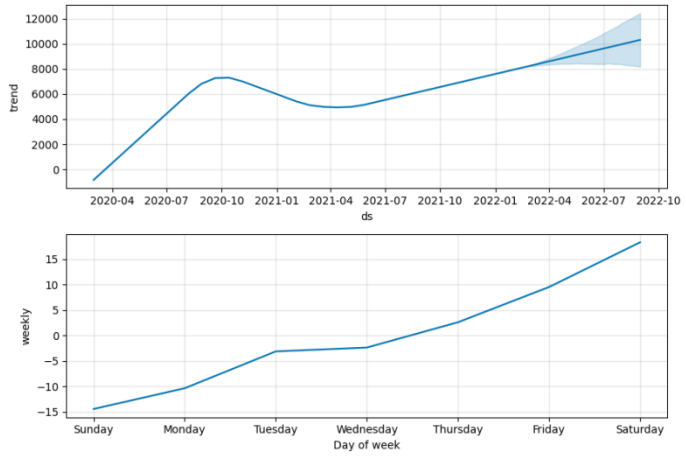


Figure 9. *Trend Component of Prophet Model*

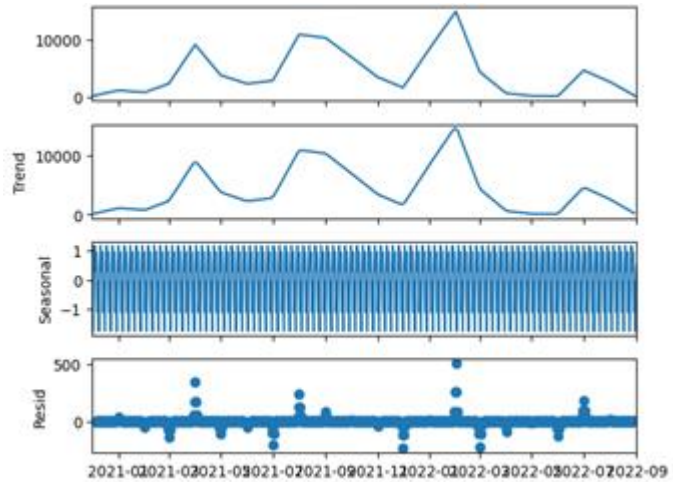


Figure 10. *Weekly Component of the Prophet Model*

The effectiveness of the DL-based LSTM model in capturing short-term dynamics is compared to that of other models. Figure 11 depicts the LSTM model's one-step forward predictions, while Figure 12 displays the 30-day projection findings. Both plots demonstrate that the LSTM model closely follows current data and accurately predicts future volatility.

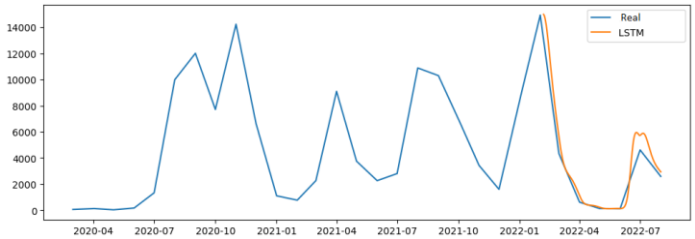


Figure 11. *One Step Forward Forecasting Results of the LSTM Model*

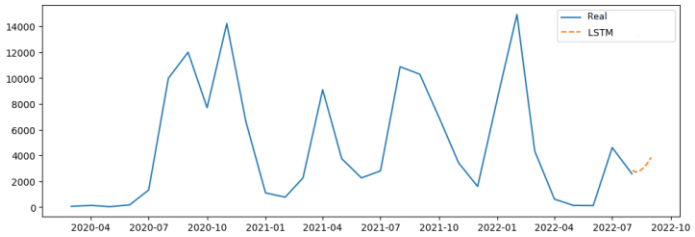


Figure 12. *30 Day Projection Forecast Results of the LSTM Model*

Table 1 summarizes the models' comparative performance findings using the error measurements. The LSTM model has the lowest error rates, with RMSE = 1.975.48 and SMAPE = 109.87%. It was followed by Log-SARIMAX (RMSE = 2 093.50; SMAPE = 114.29%) and Log-Prophet (RMSE = 5.290.28; SMAPE = 116.55%). The SARIMAX and Prophet models' error values using raw data were found to be rather high (RMSE = 33 780.25; SMAPE = 5 772.48% and RMSE = 7 014.66; SMAPE = 1 936.93%, respectively).

When examining the error metrics of all models in Table 3, the obtained RMSE and SMAPE values indicate the prediction performance of the models. The values for the models are as follows: for the LSTM model, RMSE = 1.975.48 and SMAPE = 109.87%; for the Log-SARIMAX model, RMSE = 2.093.50 and SMAPE = 114.29%; for the Log-Prophet model, RMSE = 5.290.28 and SMAPE = 116.55%; RMSE = 33,780.25 and SMAPE = 5,772.48% for the SARIMAX (raw data) model, RMSE = 7,014.66 and SMAPE = 1,936.93% for the Prophet (raw data) model.

Table 3. *Shows a comparison of model prediction performance based on error criteria.*

Model	RMSE	SMAPE (%)
LSTM	**1,975.48**	**109.87**
Log-SARIMAX	2,093.50	114.29
Log-Prophet	5,290.28	116.55
SARIMAX (Row data)	33,780.25	5,772.48
Prophet (Row data)	7,014.66	1,936.93

Discussion

In this work, three distinct techniques to modeling the change in the number of COVID-19 positive cases over time were compared: conventional statistics (SARIMAX), machine learning-based (Prophet), and deep learning-based (LSTM). The findings revealed considerable disparities in the models' representations of the series' linear and nonlinear components.

The SARIMAX model performed consistently well in short-term time series forecasting and correctly caught the series' seasonal cycles. However, the significant error variance in the SARIMAX model using raw data indicates that logarithmic treatment is required. Indeed, the log-transformed SARIMAX model gets a reduced RMSE value by homogenizing errors. This conclusion is consistent with previous research on the influence of logarithmic transformations on variance stabilization.[30]

Because of its distinct handling of trend and seasonal components, the Prophet model has performed well in interpreting the series' overall trend. The log-transformed Prophet model, in instance, produced more consistent short-term oscillations than predicted. However, the rise in the model's error rates in long-term projections suggests that Prophet's parametric structure has little flexibility in the face of unexpected trend shifts. This is further underscored by Taylor and Letham (2018), who discover that the model works best for data with substantial seasonality but suffers in the face of abrupt structural discontinuities.[21]

Because of its capacity to learn complicated and nonlinear patterns, the deep learning-based LSTM model outperformed the other models. The model's capacity to depict long-term dependence connections accounts for its excellent accuracy, particularly when dealing with rapid variations and trend breaks. This study confirms the advantages of deep learning algorithms in dynamic epidemiological data, such as COVID-19, which is heavily influenced by external influences. Similarly, the research indicates that LSTM models give forecasts with smaller prediction errors than standard statistical models.[21,30]

In general, logarithmic transformation enhances the performance of both classical and parametric models, but the LSTM model outperforms them both. This finding shows that deep learning-based algorithms are a more adaptable and powerful option for evaluating epidemiological series with abrupt swings and structural changes, such as COVID-19.

The study's results are consistent with existing literature evaluating various modeling methodologies in COVID-19 case projections. For example, the Prophet model has been shown to be very stable in short-run predictions, but DL-based models are more effective in long-run projections.[26] Similarly, it has shown that the LSTM model provides higher accuracy in predicting COVID-19 cases compared to classical statistical models.[19]

Limitations

The nature of COVID-19 data reporting in Turkey introduces several considerations when interpreting the forecasting results. Reported case numbers may have been affected by shifts in testing policies, updates to diagnostic criteria, and variations in reporting practices over time, naturally introducing fluctuations in the consistency of the series. Although cases were originally reported on a daily basis, they were aggregated into monthly totals to better observe broader trends. This transformation, while helpful for reducing noise, may have obscured short-term fluctuations and limited the models' ability to capture sudden epidemiological changes.

Relying solely on past case numbers also means that influential external factors—such as policy interventions, population mobility, and vaccination dynamics—could not be incorporated directly into the models. The 29-month observation window may further constrain the generalisability of data-driven approaches, particularly during periods of rapid change. Finally, although the logarithmic transformation improved overall model stability, it may have softened abrupt spikes, making interpretation on the original scale more challenging.

Conclusion

These results imply that when projecting epidemiological data, model selection should be carefully considered based on series structure and data dynamics.

While parametric models like SARIMAX and Prophet perform well for short-term series with consistent seasonality, the deep learning-based LSTM model is a better fit for nonlinear, variable, and complicated data structures.

This research demonstrates that deep learning models may be employed as a more effective decision support tool in healthcare planning and resource allocation procedures, utilizing COVID-19-specific regional predictions.

Authorship Contributions

Idea/Concept: E.A.G., E.G.; Control/Supervision: E.A.G., E.G.; Data Collection: E.A.G., Analysis and Interpretation: E.A.G, E.G.; Literature Review: E.A.G., E.G.; Article Writing: E.A.G.; Critical Review: E.G.; References and Funding: E.A.G.

Conflicts of interest

There are no conflicts of interest in this work.

References

1. Abade A, Porto LF, Scholze AR, et al. A comparative analysis of classical and machine learning methods for forecasting TB/HIV co-infection. *Sci Rep*. 2024;14(1):18991. doi:https://doi.org/10.1038/s41598-024-69580-4
2. Çelik Ş, Yurtbay S, Tekin YK, Korkmaz İ, Çelik P. Covid-19 Pandemisinin Acil Servis Yüküne Etkisi. *Van Tıp Der*. 2022;29(3):303-308. doi:https://doi.org/10.5505/vtd.2022.87405
3. Rehman AU, Mian SH, Usmani YS, Abidi MH, Mohammed MK. Modeling consequences of COVID-19 and assessing its epidemiological parameters: a System Dynamics Approach. *MDPI*. 2023:260.

4. Wang Y, Xu C, Yao S, et al. Estimating the COVID-19 prevalence and mortality using a novel data-driven hybrid model based on ensemble empirical mode decomposition. *Sci Rep*. 2021;11(1):21413. doi:https://doi.org/10.1038/s41598-021-00948-6
5. Özen NS, Saraç S, Koyuncu M. COVID-19 vakalarının makine öğrenmesi algoritmaları ile tahmini: Amerika Birleşik Devletleri örneği. *Avrupa Bilim ve Teknoloji Derg*. 2021;(22):134-139. doi: https://doi.org/10.31590/ejosat.855113
6. Guleryuz D. Forecasting outbreak of COVID-19 in Turkey; Comparison of Box–Jenkins, Brown's exponential smoothing and long short-term memory models. *Proc Safety Environ Protect*. 2021;149:927-935. doi:https://doi.org/10.1016/j.psep.2021.03.032
7. Zhao W, Sun Y, Li Y, Guan W. Prediction of COVID-19 data using hybrid modeling approaches. *Front in Public Health*. 2022;10:923978. doi:https://doi.org/10.3389/fpubh.2022.923978
8. Sevli O, Gülsoy VGB. Covid-19 salgınına yönelik zaman serisi verileri ile Prophet model kullanarak makine öğrenmesi temelli vaka tahminlemesi. *Avrupa Bilim ve Teknoloji Derg*. 2020;(19):827-835. doi:https://doi.org/10.31590/ejosat.766623
9. Taylor SJ, Letham B. Forecasting at scale. *The American Statistician*. 2018;72(1):37-45. doi:https://doi.org/10.7287/peerj.preprints.3190v2
10. Kaya U, Akba F, Medeni İ, Medeni T. Covid-19 öncesi ve sonrasındaki Bitcoin fiyat değişimlerinin Makine Öğrenmesi, zaman serileri analizi ve derin öğrenme yöntemleriyle değerlendirilmesi. *Bilişim Teknolojileri Derg*. 2020;13(3):341-355. doi:https://doi.org/10.17671/gazibtd.648424
11. Napoli AM, Smith-Shain R, Lin T, Baird J. The accuracy of predictive analytics in forecasting emergency department volume before and after onset of COVID-19. *Western J Emerg Med*. 2023;25(1):61. doi:https://doi.org/10.5811/westjem.61059
12. Baccega D, Castagno P, Fernández Anta A, Sereno M. Enhancing COVID-19 forecasting precision through the integration of compartmental models, machine learning and variants. *Sci Rep*. 2024;14(1):19220. doi:https://doi.org/10.1038/s41598-024-69660-5
13. Farhat F, Sohail SS, Alam MT, et al. COVID-19 and beyond: leveraging artificial intelligence for enhanced outbreak control. *Frontiers in Artificial Intelligence*. 2023;6:1266560. doi:https://doi.org/10.3389/frai.2023.1266560
14. ArunKumar K, Kalaga DV, Kumar CMS, Kawaji M, Brenza TM. Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends. *Alexandria Engineer J*. 2022;61(10):7585-7603. doi:https://doi.org/10.1016/j.aej.2022.01.011
15. Deschepper M, Eeckloo K, Malfait S, Benoit D, Callens S, Vansteelandt S. Prediction of hospital bed capacity during the COVID− 19 pandemic. *BMC Health Serv Res*. 2021;21(1):468. doi:https://doi.org/10.1186/s12913-021-06492-3
16. Ódor G, Karsai M. Epidemic-induced local awareness behavior inferred from surveys and genetic sequence data. *Nat Comm*. 2025;16(1):4758. doi:https://doi.org/10.48550/arxiv.2406.09983
17. Ali AO, Palanichamy N, Haw SC, Gopal S. Performance Evaluation on COVID-19 Prediction using Machine Learning Models. *J Inform Web Engineer*. 2025;4(2):64-76. doi:https://doi.org/10.33093/jiwe.2025.4.2.5
18. K Abdul Hamid AA, Wan Mohamad Nawi WIA, Lola MS, et al. Improvement of time forecasting models using machine learning for future pandemic applications based on COVID-19 data 2020–2022. *Diagnostics*. 2023;13(6):1121. doi:https://doi.org/10.3390/diagnostics13061121
19. Zhao D, Zhang R, Zhang H, He S. Prediction of global omicron pandemic using ARIMA, MLR, and Prophet models. *Sci Rep*. 2022;12(1):18138. doi: https://doi.org/10.1038/s41598-022-23154-4
20. Nassiri H, Mohammadpour SI, Dahaghin M. How do the smart travel ban policy and intercity travel pattern affect COVID-19 trends? Lessons learned from Iran. *Plos One*. 2022;17(10):e0276276. doi:https://doi.org/10.1371/journal.pone.0276276
21. Li X, Zhang X. A comparative study of statistical and machine learning models on carbon dioxide emissions prediction of China. *Environ Sci Pollut Res*. 2023;30(55):117485-117502. doi:https://doi.org/10.1007/s11356-023-30428-5
22. Wang Y, Xu C, Wu W, et al. Time series analysis of temporal trends in hemorrhagic fever with renal syndrome morbidity rate in China from 2005 to 2019. *Sci Rep*. 2020;10(1):9609. doi:https://doi.org/10.1038/s41598-020-66758-4
23. Chen Q, Zheng X, Shi H, et al. Prediction of influenza outbreaks in Fuzhou, China: comparative analysis of forecasting models. *BMC Public Health*. 2024;24(1):1399. doi:https://doi.org/10.1186/s12889-024-18583-x
24. Zhou L, Zhao P, Wu D, Cheng C, Huang H. Time series model for forecasting the number of new admission inpatients. *BMC Medical Informatics and Decision Making*. 2018;18(1):39. doi:https://doi.org/10.1186/s12911-018-0616-8
25. Jäger WS, Nagler T, Czado C, McCall RT. A statistical simulation method for joint time series of non-stationary hourly wave parameters. *Coastal Engineering*. 2019;146:14-31. doi:https://doi.org/10.1016/j.coastaleng.2018.11.003
26. Sharma K, Bhalla R, Ganesan G. Time Series Forecasting Using FB-*Prophet*. 2022:59-65.
27. Zunic E, Korjenic K, Hodzic K, Donko D. Application of facebook's prophet algorithm for successful sales forecasting based on real-world data. arXiv preprint arXiv:200507575. 2020;doi: https://doi.org/10.5121/ijcsit.2020.12203
28. Vo NN, He X, Liu S, Xu G. Deep learning for decision making and the optimization of socially responsible investments and portfolio. Decision Support Systems. 2019;124:113097. doi:https://doi.org/10.1016/j.dss.2019.113097
29. Woltmann L, Deepe J, Hartmann C, Lehner W. evalPM: a framework for evaluating machine learning models for particulate matter prediction. *Environ Monit Assess*. 2023;195(12):1491. doi:https://doi.org/10.1007/s10661-023-11996-y
30. Bandara K, Bergmeir C, Smyl S. Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. *Expert Systems with Applications*. 2020;140:112896. doi:https://doi.org/10.1016/j.eswa.2019.112896