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Original Article

Application of the SARIMA-LSTM model to evaluate the effectiveness of interventions for Visceral Leishmaniasis

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Abstract

Introduction: This study proposes a combined Seasonal Autoregressive Integrated Moving Average and Long Short-Term Memory (SARIMA-LSTM) model to enhance the accuracy of evaluating the effectiveness of visceral leishmaniasis prevention and control efforts in Yangquan, China.

Methodology: Data were obtained from the Yangquan Centre for Disease Control and Prevention. The hybrid model integrates a SARIMA component with a residual-based LSTM neural network.

Results: In the SARIMA-LSTM model, the LSTM component included seven hidden layer nodes, a learning rate of 0.001, 500 training epochs, a batch size of 256, and utilized the Adam optimization algorithm. The SARIMA-LSTM model demonstrated superior performance (MSE = 2.824, MAE = 1.279, RMSE = 1.681). A paired samples t-test revealed a statistically significant difference between predicted and actual case counts (t = -4.058, p < 0.001), indicating that the actual number of cases was lower than predicted.

Conclusions: The combined SARIMA-LSTM model outperformed the individual SARIMA and LSTM models, suggesting that the implemented interventions were generally effective.

Key words: Visceral leishmaniasis; SARIMA-LSTM model; effectiveness evaluation; Yangquan.

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Introduction

Visceral leishmaniasis is a chronic, endemic disease caused by infection with *Leishmania donovani* protozoa, transmitted through the bite of a Phlebotomus sandfly [1]. Although China declared the near-eradication of visceral leishmaniasis in 1958 [2], its incidence has increased in Shanxi Province in recent years. From 2019 to 2020, Shanxi reported the highest number of cases at the provincial level, with Yangquan City accounting for the largest proportion [3].

In response to the resurgence, the Yangquan Centre for Disease Control and Prevention (CDC) implemented a series of preventive and control measures in May 2020. These included population screening, culling of infected dogs, elimination of Phlebotomus vectors, and the enhancement of public education to improve awareness of prevention, control, and self-protection. A rigorous scientific evaluation of these interventions is essential. A simple comparison of pre- and post-intervention incidence rates is insufficient for accurate assessment, highlighting the need for more sophisticated statistical approaches. Time-series forecasting models utilize historical data to identify and model trends, capturing the seasonality commonly observed in the incidence of infectious diseases [4]. Among these models, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is widely used for its effectiveness in fitting linear time-series data [5]. However, the SARIMA model is limited in capturing nonlinear patterns. Its use of differencing to address non-stationarity may result in information loss and decreased predictive accuracy [6].

To overcome these limitations, neural network-based methods such as Long Short-Term Memory (LSTM) have been introduced in time-series modeling. LSTM is particularly effective in modeling nonlinear relationships and long-term dependencies in sequential data [7]. When combined with SARIMA, the resulting hybrid model has shown improved fitting and forecasting performance [8].

To more accurately evaluate the effectiveness of visceral leishmaniasis prevention and control in Yangquan, a combined SARIMA-LSTM model was developed. Its performance was compared with standalone models, and the post-intervention incidence was predicted. The effectiveness of the interventions was assessed by comparing the predicted incidence with the actual reported cases.

Methodology

Data Sources

Monthly records of visceral leishmaniasis cases from January 2017 to December 2021 were obtained from the Yangquan Centre for Disease Control and Prevention (CDC).

Construction of SARIMA-LSTM Models

SARIMA Model

The SARIMA model was developed using data from January 2017 to April 2020. Fitted values were generated, and residuals were computed as the difference between actual and fitted values. As first-order differencing was applied, the initial month was excluded from the residual analysis, yielding residuals from February 2017 to April 2020.

Residual LSTM Model

Residuals obtained from the SARIMA model were used to construct the residual LSTM model. The training set comprised data from February 2017 to December 2019, while the validation set included data from January to April 2020. The sliding window method was employed for model construction and optimization. Although intelligent optimization algorithms can be used for hyperparameter tuning [9], a heuristic approach based on empirical experience and validation performance was adopted due to the limited dataset size. Similar strategies have been applied in forecasting models for brucellosis and influenza [8,10].

Model Combination

The SARIMA model was first used to predict visceral leishmaniasis cases from May 2020 to December 2021. The residual LSTM model then forecasted residuals for the same period using the sliding window method. Predicted residuals were inverse-normalized and added to SARIMA predictions to obtain the final output of the combined model.

Evaluation of Model

Model performance was assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Lower values for these metrics indicate superior model performance.

Evaluation of Intervention Effectiveness

The optimal model was used to forecast cases from May 2020 to December 2021, and predicted values were compared with the actual reported cases. Statistically significant differences indicated effectiveness of the intervention measures.

Statistical Analysis

SPSS 26.0 software was used for normality tests and analysis of variance, while Anaconda 4.10.3 was used to construct the SARIMA, LSTM, and SARIMA-LSTM models. Statistical significance was set *at* $p < 0.05$.

Results

Data Overview

In the data description section of this paper, reference is made to the format in the article by Yalınbaş *et al.* [11], which accurately characterizes the data. A total of 239 cases of visceral leishmaniasis were reported in Yangquan City, Shanxi Province, from January 2017 to December 2021, corresponding to an average annual incidence rate of 3.43 per 100,000. Of these, 166 cases occurred in males (4.63/100,000) and 73 in females (2.16/100,000), indicating a higher incidence in males. Patient ages ranged from 9 months to 85 years. Farmers represented 43.51% of all reported cases.

SARIMA Model

Stationarity and randomness tests were conducted on the original time series. The Ljung–Box test indicated non-randomness ($\chi^2 = 7.710$, $p < 0.001$), and the Augmented Dickey–Fuller (ADF) test indicated non-stationarity ($t = 0.623$, $p = 0.988$). First-order differencing was applied to achieve stationarity (ADF test $t = -2.871$, $p = 0.04$) (Table 1). A SARIMA (p,1,q) $(P,0,Q)_{52}$ model was explored.

We used p, P, q, Q = 0:2 and used Grid Search to obtain the minimum value of AIC, thus finalizing the model parameters as SARIMA (1,1,2) $(2,0,2)_{52}$ and AIC = 49.808. The model passed the residual white noise test ($\chi^2 < 0.001$, $p = 0.980$) (Table 2).

Table 1. ADF and Ljung-Box tests of the time series.

Time series	ADF		Ljung-Box	
	t	p	$\chi 2$	p
Original series	0.623	0.988	7.710	< 0.001
Adjusted series	-2.871	0.049	8.693	< 0.001

Table 2. SARIMA model parameter estimation.

Model	Model parameter							Ljung-Box		AIC
	AR1	*MA1*	*MA2*	*SAR1*	*SAR2*	*SMA1*	*SMA2*	$\chi 2$	*p*	
(1,1,2) (2,0,2) $_{52}$	-0.936	0.962	1.000	0.456	0.387	1.414	1.000	< 0.001	0.980	49.808

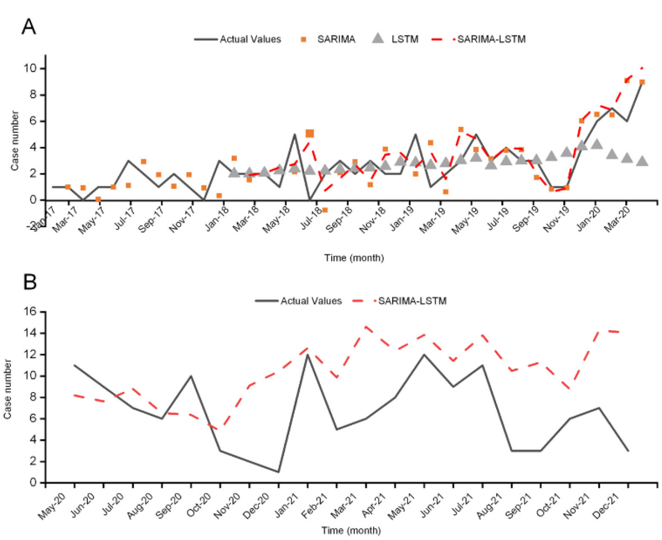
LSTM Model

The dataset was processed using a sliding window of length 12, where 12 previous observations were used to predict the next point (12 input nodes, 1 output node). The optimal model was obtained with 13 hidden nodes, yielding the lowest MSE, MAE, and RMSE on the validation set (Table 3). Final hyperparameters included 13 hidden nodes, a learning rate of 0.001, 500 training epochs, a batch size of 256, and the Adam optimizer.

SARIMA-LSTM Model

Fitted values for February 2017 to April 2020 were generated using the SARIMA (1,1,2) $(2,0,2)_{52}$ model. Residuals were modeled using an LSTM with training data from February 2017 to December 2019 and validation data from January to April 2020. The number of hidden nodes ranged from 4 to 14, with 7 yielding optimal performance based on validation metrics (Table 4). The residual LSTM was then applied using 7 hidden nodes, a learning rate of 0.001, 500 training epochs, a batch size of 256, and the Adam optimizer. The final SARIMA-LSTM fitted values were obtained by summing SARIMA predictions and residual LSTM outputs.

Figure 1. Analysis and prediction of visceral leishmaniasis cases using SARIMA, LSTM, and SARIMA-LSTM model. **A.** Performance comparison of SARIMA, LSTM, and SARIMA-LSTM models; **B.** Predicted versus actual visceral leishmaniasis cases using the SARIMA-LSTM model.



Comparison of Model Performance

All three models were used to fit data from January 2017 to April 2020. As shown in Figure 1A, the SARIMA-LSTM model provided the best fit to the observed data. Evaluation metrics (Table 5) confirmed its superior performance, with the lowest MSE, MAE, and RMSE values.

Evaluation of Intervention Effectiveness

The SARIMA-LSTM model was used to forecast cases from May 2020 to December 2021. Predicted values were compared with actual case numbers. Differences were normally distributed (z = 0.965, p =

Table 3. Error distribution of the number of nodes in the hidden layer of the LSTM model in the validation set.

Number of nodes	*MSE*	*MAE*	*RMSE*
4	17.9721	4.0655	4.2393
5	18.3973	4.0850	4.2892
6	18.1460	4.1100	4.2598
7	18.3421	4.0466	4.2828
8	16.8447	3.9459	4.1042
9	15.8623	3.8236	3.9827
10	16.6062	3.8853	4.0751
11	15.4707	3.6386	3.9333
12	15.7021	3.7583	3.9626
13	**15.4510**	**3.5990**	**3.9308**
14	15.7018	3.7770	3.9626

bold text represents the optimal number of nodes.

Table 4. Error distribution of the number of nodes in the hidden layer of the residual LSTM model in the validation set.

Number of nodes	*MSE*	*MAE*	*RMSE*
4	3.3732	1.4727	1.8366
5	3.9738	1.6649	1.9934
6	3.3588	1.4332	1.8327
7	**3.2230**	**1.4090**	**1.7953**
8	3.2841	1.5024	1.8122
9	3.4247	1.5271	1.8506
10	3.3197	1.4758	1.8220
11	4.3707	1.8116	2.0906
12	3.8667	1.6486	1.9664
13	4.1358	1.7286	2.0337
14	3.5188	1.5762	1.8759

Bold text represents the optimal number of nodes.

Table 5. Performance comparison of the three models.

Model	*MSE*	*MAE*	*RMSE*
SARIMA	2.995	1.318	1.731
LSTM	3.623	1.310	1.903
SARIMA-LSTM	**2.824**	**1.279**	**1.681**

Bold text represents the optimal number of nodes.

Table 6. Results of paired samples *t*-test.

	Mean	*s*	*t*	*v*	*p*
Difference	−3.583	3.95	−4.058	19	< 0.001

0.654), and a paired-sample t-test revealed a statistically significant difference ($t = -4.058$, $p < 0.001$) (Table 6), with a large effect size (Cohen's d = 0.91). Figure 1B illustrates a visible decrease in visceral leishmaniasis cases following the intervention, supporting the effectiveness of the control measures implemented by the Yangquan CDC.

Discussion

To address the annual rise in reported cases of visceral leishmaniasis, the Yangquan Centre for Disease Control and Prevention (CDC) implemented a series of active prevention and control measures. Developing accurate and reliable models to evaluate the effectiveness of these interventions is essential for guiding disease management strategies and informing public health policymaking [12]. The observed seasonal pattern in visceral leishmaniasis cases is likely attributable to the peak activity period of Phlebotomus sandflies, typically from May to June, which facilitates disease transmission. Therefore, May represents an optimal window for residual insecticide spraying to reduce vector density.

The SARIMA model, a classical time series approach, has demonstrated high stability and forecasting accuracy across numerous empirical studies, establishing it as a standard benchmark for evaluating alternative models [13]. Long Short-Term Memory (LSTM) neural networks have also shown robust performance in modeling temporal patterns. However, as highlighted by several studies, no single model can be considered universally superior [14]. The dynamics of infectious diseases are governed by complex, often nonlinear interactions. Consequently, individual models tend to capture only specific aspects of the underlying patterns, frequently falling short of the accuracy required for time series prediction.

In response to these challenges, the integration of predictive models has emerged as a mainstream strategy for improving time series forecasting. In the field of infectious disease modeling, hybrid models such as ARIMA-SVR and ARIMA-GRNN have demonstrated superior performance compared to their single-model counterparts [15,16]. Consistent with this trend, the present study first developed a SARIMA (1,1,2) (2,0,2) 52 model as a benchmark. Although the SARIMA model produced forecasts that closely aligned with observed data, notable discrepancies remained—primarily due to its capacity to capture linear relationships while lacking the flexibility to model nonlinear components [17].

To address this limitation, an LSTM model was trained on the residuals of the SARIMA model to capture the nonlinear information not explained by the linear component. The resulting SARIMA-LSTM hybrid model demonstrated superior predictive performance compared to the SARIMA and LSTM models individually. This finding is in line with previous research [7,10,18], underscoring the advantages of hybrid modeling in infectious disease forecasting. The SARIMA-LSTM approach holds promise for predicting other infectious diseases or for application in different geographic regions affected by visceral leishmaniasis. The Yangquan Municipal Government's comprehensive intervention strategies—particularly the identification and removal of infected canines—have proven effective. Infected dogs serve as the primary reservoir for *Leishmania donovani* and are the main source of human transmission. Eliminating infected dogs can significantly reduce the risk of vector-borne transmission. Numerous studies have also shown that the use of chemical and biological agents to eradicate sandflies effectively reduces the incidence of visceral leishmaniasis. Environmental management, when combined with vector control efforts, plays a crucial role in disrupting local transmission chains and preventing new infections [19]. Moreover, public awareness campaigns are vital. Educating the public on preventive behaviors—such as using insect repellents and wearing protective clothing—can significantly lower infection risk, especially in resource-limited settings [20].

This study has several limitations. First, although infectious diseases are influenced by multiple factors—including climatic variables (e.g., temperature and humidity) and socio-economic conditions—only historical incidence data were used in the model. Future studies should consider incorporating additional explanatory variables to improve predictive performance. Second, while this study compared selected models, the performance of other advanced modeling approaches was not assessed. Finally, although the intervention's overall effectiveness was evaluated, the individual contributions of specific measures were not quantified.

Conclusions

The combined SARIMA-LSTM model demonstrated superior performance compared to the standalone SARIMA and LSTM models, offering enhanced accuracy in forecasting visceral leishmaniasis cases. These findings support the broad effectiveness of the intervention measures implemented by the Yangquan CDC and highlight the potential utility of hybrid modeling approaches in infectious disease surveillance and control.

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Ethical Approval

The work did not need ethical approval as no study of patients or communities was undertaken.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflict of interests

No conflict of interests is declared.

References

1. Cloots K, Uranw S, Ostyn B, Bhattarai NR, Le Rutte E, Khanal B, Picado A, Chappuis F, Hasker E, Karki P, Rijal S, Boelaert M (2020) Impact of the visceral leishmaniasis elimination initiative on *Leishmania donovani* transmission in Nepal: a 10-year repeat survey. Lancet Glob Health 8: e237–e243. doi: 10.1016/S2214-109X(19)30536-4.
2. Leng YJ (1982) A review of kala-azar in China from 1949 to 1959. Trans R Soc Trop Med Hyg 76: 531–537. doi: 10.1016/0035-9203(82)90157-2.
3. Dal P, Tian X, Zhao J, Dong H, Cheng J (2022) Epidemiological characteristics of visceral leishmaniasis in Shanxi province, China, 2020. Chin. J. Vector Bio. Control 33: 405–408. doi: 10.11853/j.issn.1003.8280.2022.03.017.
4. Wu W, An S-Y, Guan P, Huang D-S, Zhou B-S (2019) Time series analysis of human brucellosis in mainland China by using Elman and Jordan recurrent neural networks. BMC Infect Dis 19: 414. doi: 10.1186/s12879-019-4028-x.
5. Zhang R, Song H, Chen Q, Wang Y, Wang S, Li Y (2022) Comparison of ARIMA and LSTM for prediction of hemorrhagic fever at different time scales in China. PLoS One 17: e0262009. doi: 10.1371/journal.pone.0262009.
6. de Oliveira JFL, Ludermir TB (2016) A hybrid evolutionary decomposition system for time series forecasting. Neurocomputing 180: 27–34. doi: 10.1016/j.neucom.2015.07.113.
7. Song W, Gao C, Zhao Y, Zhao Y (2020) A time series data filling method based on LSTM-taking the stem moisture as an example. Sensors (Basel) 20: 5045. doi: 10.3390/s20185045.
8. Zhai M, Li W, Tie P, Wang X, Xie T, Ren H, Zhang Z, Song W, Quan D, Li M, Chen L, Qiu L (2021) Research on the predictive effect of a combined model of ARIMA and neural networks on human brucellosis in Shanxi Province, China: a time series predictive analysis. BMC Infect Dis 21: 280. doi: 10.1186/s12879-021-05973-4.
9. Yenilmez İ, Akçay EK (2023) Performance of particle swarm optimization and genetic algorithm for tuning of k-NN hyperparameters. Akdeniz 10th International Conference on Applied Sciences. 328-338.
10. Zhao Z, Zhai M, Li G, Gao X, Song W, Wang X, Ren H, Cui Y, Qiao Y, Ren J, Chen L, Qiu L (2023) Study on the prediction effect of a combined model of SARIMA and LSTM based on SSA for influenza in Shanxi Province, China. BMC Infect Dis 23:71. doi: 10.1186/s12879-023-08025-1.
11. Yalınbaş B, Dizen H, Yenilmez İ (2022) Evaluation of clinical features and risk factors affecting bleeding in patients with gastrointestinal angiodysplasia. Ankara Eğitim ve Araştırma Hastanesi Tıp Dergisi 55: 120–124. doi:10.20492/aeahtd.1088748. [Article in Türkçe].
12. Zhang J, Wang X, Chen S (2023) Study on the interaction between information dissemination and infectious disease dissemination under government prevention and management. Chaos Solitons Fractals 173: 113601. doi: 10.1016/j.chaos.2023.113601.
13. Dubey AK, Kumar A, García-Díaz V, Sharma AK, Kanhaiya K (2021) Study and analysis of SARIMA and LSTM in forecasting time series data. Sustainable Energy Technol. Assess. 47: 101474. doi: 10.1016/j.seta.2021.101474.
14. Yenilmez İ, Mugenzi F (2023) Estimation of conventional and innovative models for Rwanda's GDP per capita: A comparative analysis of artificial neural networks and Box–Jenkins methodologies. Scientific African 22: e01902. doi: 10.1016/j.sciaf.2023.e01902.

15. Wei W, Jiang J, Liang H, Gao L, Liang B, Huang J, Zang N, Liao Y, Yu J, Lai J, Qin F, Su J, Ye L, Chen H (2016) Application of a combined model with autoregressive integrated moving average (ARIMA) and generalized regression neural network (GRNN) in forecasting hepatitis incidence in Heng County, China. PLoS One 11: e0156768. 15. doi: 10.1371/journal.pone.0156768.
16. Norrulashikin MA, Yusof F, Hanafiah NHM, Norrulashikin SM (2021) Modelling monthly influenza cases in Malaysia. PLoS One 16: e0254137. doi: 10.1371/journal.pone.0254137.
17. Zeng T, Xie N, Ramziya R, Wang T (2021) Prediction of epidemic trend of mumps in Kashgar area based on SARIMA-SVR model. Modern Preventive Medicine 48: 2139–2143
18. Mbah TJ, Ye H, Zhang J, Long M (2021) Using LSTM and ARIMA to simulate and predict limestone price variations. Min Metall Explor 38: 913–926. doi: 10.1007/s42461-020-00362-y.
19. Berhe R, Spigt M, Schneider F, Paintain L, Adera C, Nigusie A., Gizaw Z., Tesfaye Y, Elnaiem DA, Alemayehu M (2022) Understanding the risk perception of visceral leishmaniasis exposure and the acceptability of sandfly protection measures among migrant workers in the lowlands of Northwest Ethiopia: a health belief model perspective. BMC Public Health 22: 989. 19. doi: 10.1186/s12889-022-13406-3.
20. Doe ED, Egyir-Yawson A, Kwakye-Nuako G (2019) Knowledge, attitude and practices related to cutaneous leishmaniasis in endemic communities in the Volta region of Ghana. Int J Healthc Sci 7: 12.