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Short-Term Forecasting of Meningitis Outbreaks in Nigeria Using Hybrid PSO-LSTM and GA-LSTM: A Case Study of Zamfara State

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ABSTRACT

Meningitis outbreaks continue to be a public health problem in Nigeria, especially in the African meningitis belt, which experiences frequent epidemics in the dry season. The focus of this study is on short-term monthly forecasting of meningitis cases, rather than diagnostic classification, which has been more extensively studied. The particle swarm optimisation–long short-term memory (PSO-LSTM), genetic algorithm–long short-term memory (GA-LSTM), conventional LSTM, autoregressive integrated moving average (ARIMA), linear regression (LR), and Random Forest (RF) were developed and compared. The Nigeria Centre for Disease Control (NCDC) provided monthly confirmed meningitis surveillance data from January 2017 to May 2019 (29 observations) from the Zamfara State of Nigeria. As regards the held-out test data, the manually tuned LSTM outperformed other models in terms of MSE, RMSE, and MAE of 13.711, 3.703, and 2.436, respectively. It outperformed GA-LSTM (14.871, 3.856, 2.539), PSO-LSTM (18.105, 4.255, 2.827), RF (60.152, 7.756, 4.475), ARIMA (72.404, 8.509, 6.011), and LR (107.648, 10.375, 6.484). Despite some optimism, the manually tuned LSTM was not improved after training using the metaheuristic optimisation. However, all models based on LSTM clearly outperformed the classical models, suggesting that LSTM models can provide signals for short-term forecasting from a small amount of time-series data on the meningitis. This study underscores the significance of taking into account the number of data available, the lead time and geographic coverage when planning machine-learning based EWS.

Keywords: LSTM; PSO-LSTM; GA-LSTM; ARIMA; Meningitis Outbreak; Time Series Forecasting; Nigeria

Abbreviations: PSO-LSTM: Particle Swarm Optimisation–Long Short-Term Memory; GA-LSTM: Genetic Algorithm–Long Short-Term Memory; ARIMA: Autoregressive Integrated Moving Average; Linear Regresion; NCDC: Nigeria Centre for Disease Control; RF: Random Forest; ML: Machine Learning; AR: Auto Regression; SME: Squared Average Error

Introduction

Meningitis is inflammation of the membranes (meninges) that surround the central nervous system (brain and spinal cord) [1]. Aetiology involves a range of infectious agents including bacteria, viruses, fungi and parasites alongside non-infectious factors and these can include some drugs or underlying medical conditions [2,3]. Bacterial meningitis is a severe and potentially fatal disease, and in Nigeria the most common bacterial pathogen associated with outbreaks of meningitis disease is Neisseria meningitidis (particularly serogroup C) and Haemophilus influenzae which contributes significantly to the incidence of meningitis among children and other vulnerable groups. The clinical picture of viral meningitis is unique with a more benign outcome that is often not treated specifically and is commonly caused by enteroviruses and the mumps virus [4,5]. Although rare, fungal and parasitic meningitis can occur and is more common in those with compromised immune systems, while non-infectious causes of meningitis (malignancy, some medicines and head injuries) can also cause it [6]. The clinical features of meningitis can vary considerably with the age of the patient and aetiology of the disease.

Common symptoms are sudden onset of high fever, severe headache, stiff neck, vomiting, sensitivity to light, confusion, and in a few cases, skin rash especially associated with meningococcal meningitis [7]. Infants may alternatively show signs of increased irritability, poor feeding and bulging fontanelle [8]. Even though the incidence of meningitis has reduced over time, it continues to be a public health problem in Nigeria due to its geographical position in sub-Saharan Africa where there are increased risks of widespread meningitis outbreaks [9,10]. Dry season (December to June, depending on the area) is when the disease is most likely to be epidemic, with hot and dry winds, and increased strains of living conditions, making it more likely to spread [11,12]. Nigeria is part of the African meningitis belt which stretches from Senegal to Ethiopia, the most affected area in the world with respect to meningococcal meningitis [13,14]. Nigeria has had some of the biggest meningitis epidemics on record: Suspected cases of meningitis were more than 14,000 and deaths reached nearly 1,200 during the 2016-2017 epidemic. Certain risk factors for CA-BM are known, such as age, immune status and overcrowding [15] and if left untreated, the disease can be fatal or cause survivors to suffer from permanent disabilities, including hearing loss, neurological damage, and cognitive disability, especially children <5 years of age [16].

Defining an Outbreak

However, this study adopts Nigeria Center for Disease Control (NCDC) operational surveillance convention for outbreak of meningitis, that is, when the number of confirmed cases in a LGA is higher than the expected seasonal baseline of a LGA over a fixed operational time frame. The numeric threshold is based on population size and outlined in NCDC's meningitis technical guidelines. This analysis, which models the monthly numbers of confirmed cases, rather than using a binary classification of outbreaks versus non-outbreaks, retains the full graded information in the time series. The rationale for this design feature and its impact on the "Accuracy" measure is explored more in the manuscript.

Machine Learning in Meninsgitis Detection and Prediction

Machine learning (ML) has proven to be a valuable tool in detecting and predicting meningitis and several studies have demonstrated high diagnostic accuracy for ML algorithms. Deep Generative Decision Neural Network (DGDN2) has been shown to have a high accuracy in predicting whether a disease is diagnosed as meningitis or not [17]. Logistic regression and multiple logistic regression algorithms were the most commonly used algorithms in sixteen studies used to detect a diagnosis, with significant enhancements in diagnostic accuracy reported for these algorithms [18]. In addition, other methods such as Random Forest and support vector machines are effective in performing prediction tasks related to meningitis [19] as well as Extreme Gradient Boosting and explainable-AI methods [20], multilayer regression, Random Forest and naïve bayes [21] and ensemble methods with decision trees [22]. Although ML has great potential to enhance the diagnosis and prediction of meningitis, there are still numerous issues to be addressed regarding the generalisability of the models and issues of data quality, and additional research is required to test the ability of these algorithms in various clinical and surveillance settings.

Predicting infectious disease outbreaks traditionally has been done through surveillance systems and compartmental epidemiological models, although these are useful they cannot flexibly learn non-linear temporal patterns directly from routinely collected case data, as is done here. This research aims to determine whether a metaheuristic optimised LSTM network (PSO-LSTM and GA-LSTM) can achieve better performance than a conventional, manually tuned LSTM network and classical statistical models (ARIMA) and regression (linear regression and Random Forest) models for short-term forecasting of confirmed meningitis cases in a Nigerian state. Our strong assumption, based on the wider swarm- and evolution-based hyperparameter search literature, has been that LSTM configurations obtained by swarm- and evolution-based hyperparameter search would generalise at least as well as – and possibly better than –LSTM hyperparameters being manually tuned using heuristic knowledge. Zamfara State was chosen as the case study state because it has a long history of confirmed reporting of meningitis in the 2017–2019 period spanned by the NCDC dataset used here and a sufficient number of confirmed cases, so as to begin to demonstrate an initial use of the forecasting pipeline; in the results and discussion section, the discussion of the limitation of the single-state case study does not imply that it cannot be generalised to the other 36 states in Nigeria. The main contributions of this paper are as follows:

(i) The existing literature on machine learning models for forecasting meningitis outbreaks is limited, mainly concentrating on machine learning models as diagnostic classifiers for meningitis, instead of as future case count forecasting tools.

(ii) Six forecasting models are implemented and compared using a common evaluation protocol to forecast the number of cases of meningitis in the short term: PSO-LSTM, GA-LSTM, conventional LSTM, ARIMA, linear regression, and Random Forest.

(iii) Short Time Forecasting Capacity: The models were tested with regards to their short time forecasting capacity, that is, the forecasting horizon was out of sample, which was seen as a useful tool for health authorities to ensure pre-emptive intervention planning.

(iv) An honestly reported comparative finding: Our initial hypothesis that conventional manually tuned LSTM would outperform the two metaheuristic-optimised LSTM hybrids (PSO-LSTM and GA-LSTM) was wrong, and despite the fact that the result was a negative for the optimisation of the LSTM model, we report it in this paper to highlight the negative effect of the optimisation on this dataset.

(v) Real surveillance data: The study utilizes monthly real surveillance data of confirmed cases from Nigeria Centre for Disease Control (NCDC) for 2017–2019 which makes the results pertinent to a real Nigerian surveillance context.

Related Works

There is a large body of epidemiological information that shows the size and timing of the meningitis burden in Nigeria and gives a background to the present forecasting study. Omoleke and Kanmodi [9] studied the periodic occurrence of meningococcal meningitis outbreaks in Nigeria and recommended for the accelerated introduction of a conjugated meningococcal vaccine into the National Routine Immunization Schedule, indicating that the seasonality of the meningitis outbreaks during the dry season, which is exploited implicitly by the time series models used in the present study, is an epidemiological feature rather than a feature of the data set. Okolie and Essien [13] examined laboratory diagnostic capacity throughout the meningitis belt region of sub-Saharan Africa and identified that diagnostic/reporting capacity was an important determinant of the number of reported "confirmed cases"—which are used in the NCDC dataset underlying this study. On a broader scale, Chen, et al. [10] found a strong worldwide correlation between the variability of temperature and incidence of meningitis, and Abbink, et al. [16] provided a general overview of the context of infectious disease response in sub-Saharan Africa in terms of public health and governance. These studies all support the idea that meningitis incidence can be considered a true seasonal, climate-driven signal that can be forecasted using time series models and warns against assuming that raw incidence data is a straightforward signal due to the presence of surveillance capacity artefacts.

Machine Learning for Diagnosing, Predicting and Decision Support in Meningitis

Previous machine learning studies on meningitis can be broadly classified into one of three categories: diagnostic-focused classification, outbreak forecasting, and decision support/dashboard systems, which are described below thematically and contrasted in Table 1.

Table 1: Comparison of prior machine learning studies on meningitis with the present study.

Study	Disease Focus	Task	Data Source	Method(s)	Horizon	Reported Performance
Alile & Bello [26]	Meningococcal meningitis	Diagnosis	Clinical	Bayesian belief network	N/A	High accuracy (not externally validated)
Tian, et al. [27]	Meningitis	Diagnosis	Synthetic	SVM, KNN, NN, LR, RF	N/A	>95% accuracy (NN, LR)
Guzmán-de-los-Riscos, et al. [22]	Meningitis (aetiology)	Diagnosis	Clinical	Ensemble (RF/AdaBoost/GB)	N/A	High precision/recall/AUC
Šeho et al. [29]	Meningitis	Diagnosis	Clinical (n=1000)	Neural network	N/A	96.69% accuracy
Odelami [28]	Meningitis	Diagnosis	Synthetic	MLP	N/A	Accuracy (not specified)
Babatunde, et al. [23]	Cerebrospinal meningitis	Outbreak + decision support	Environmental/climatic	Logistic regression	N/S	Not fully reported
Ribeiro, et al. [25]	Meningitis	Outbreak forecasting	Case series	Decomposition + MOO	Multi-step	Improved vs. traditional
Alamo, et al. [24]	COVID-19 (cross-disease)	Monitoring/decision support	Pandemic surveillance	Data-driven/AI review	N/A	N/A (review)
This study	Meningitis	Outbreak forecasting	NCDC cases, 2017–2019	PSO-LSTM, GA-LSTM, LSTM, ARIMA, LR, RF	Short-term, out-of-sample	LSTM best: MSE 13.711, RMSE 3.703, MAE 2.436

Diagnosis-Focused Machine Learning

Most previous ML research on meningitis has been in the context of classification rather than forecasting an outbreak. Alile and Bello [23] used a Bayesian belief network to diagnose meningococcal meningitis, reporting good diagnostic accuracy but data limitations and noting that there was no external clinical validation, but importantly their work focused on diagnosis of individual patients and not on the occurrence of an outbreak at the population level. Tian, et al. [24] applied a set of classifiers to diagnosing individual patients, including SVM, k-nearest neighbours, neural networks, logistic regression and Random Forest, with over 95% classification accuracy reported for neural networks and logistic regression, however, the work was conducted using synthetic, rather than real, surveillance data, and, like Alile and Bello, intended for diagnosis rather than outbreak prediction, as is made clear in the title and in the framing of the paper. Guzmán-de-los-Riscos, Belmonte-Martínez and Lélis Carvalho [22] compared ensemble techniques, including a potential Random Forest, AdaBoost and Gradient Boosting, for the aetiology diagnostics of meningitis, which yielded high precision, recall and AUC values in a

diagnostic setting; however, the authors used a single train/test evaluation without testing the algorithm on independent test data, consisting of 1000 subjects. Another study by Odelami, et al. [25] also employed a multilayer perceptron (MLP) classifier, but on synthetic data to diagnose meningitis. One of these restrictions across the theme is, that the diagnostic classification of individual patients is not, in itself, a population-level predictive assessment of the size of future cases, which is the focus of the present study.

Forecasting-Focused Machine Learning

There is comparatively little research directly focused on meningitis. Mariani and dos Santos Coelho [26] created a multi-step-ahead method for predicting meningitis cases, which is based on a decomposition of the time series into trend, seasonal and residual components, in addition to a multi-objective optimisation technique, and found it to be better performing than traditional techniques; this approach, however, does not consider exogenous factors like climate, vaccination campaigns or population movements, which the authors observe may reduce its robustness when applied in the real world. To our knowledge, Ribeiro, et al. [26] is the most directly comparable previous forecasting study, which is done by comparing the performance of metaheuristic-optimised LSTM hybrids with a classic LSTM and classic statistical/regression models in only one evaluation protocol, as well as reporting a negative performance result for metaheuristic optimisation, rather than just a positive one, as done in Ghaddaripouri, et al. [18] study.

Environmental, Climate-Driven and Decision-Support Approaches

Another theme focuses on factors other than accuracy, such as environmental drivers and decision-support delivery. Babatunde, Adigun, et al. [27] built a logistic regression model to predict the likelihood of occurrence of an outbreak of cerebrospinal meningitis using historical environmental and climatic data; their model was made available to health care workers via a web interface, again without stating whether they used regularisation or cross-validation to reduce the possibility of overfitting on what is likely a small dataset, which is a limitation shared with the present study. Alamo, et al. [28] conducted a review on data-driven approaches for pandemic monitoring, modelling, and management, using the pandemic COVID-19 to exemplify how big data analytics, AI, and ML can be used to inform public health decision-making; while their review focused on the COVID-19 pandemic, they emphasize that models optimized to a particular pandemic may require significant adaptation to transfer to another disease, and this is equally true when considering transferring meningitis-specific forecasting models between states/countries. The studies reviewed are compared in, on the dimensions relevant to the contribution of this study. The two gaps are clearly visible at a first glance. First, most of the previous ML research in the context of meningitis focuses on diagnosis and only one exception, Ribeiro, et al. [26], aims at outbreak forecasting. Second, no previous study has directly compared the performance of the metaheuristic-optimised LSTM hybrids, PSO-LSTM or GA-LSTM, with a manually tuned LSTM and statistical/regression baselines for the specific problem of forecasting meningitis, or whether metaheuristic optimisation improves upon manual tuning for this task.

Materials and Methods

Random Forest

Random Forest is a common ensemble learning algorithm that is used in classification and regression. It trains multiple decision trees and, in the case of regression, returns the average prediction from the trees. The overall accuracy of the Random Forest is good because the ensemble method minimizes the overfitting problem by computing the average of the results from all the trees, giving a good balance between the bias and variance [29]. Random Forest is sensitive to noise in the data, to a much lesser extent than individual decision trees, since noise will be ignored when many trees are combined. Additionally, the feature-importance estimates output from Random Forest can be helpful for interpretability and feature selection [30], and the tree-based nature of the model allows for capturing complex, non-linear interactions between features [31]. Random Forest does not need to normalise or standardise the input features. The parameters of the Random Forest were fine-tuned using a grid search, and the optimized parameters were n_estimators = 30 and max_depth = 15.

Linear Regression

One of the most used statistical techniques to model the relationship between a continuous dependent variable and one or more independent variables is linear regression, if this relationship is assumed to be approximately linear. The independent (predictor) variable(s) (denoted X (or X_1, X_2, …, X_n if there are multiple independent variables), is what is used to make a prediction of the dependent (response) variable (denoted Y). However, in the univariate time series case, used here, the predictors are the lags of the case count, and the model is a linear model that estimates the current month's cases as a linear function of the cases in the previous months. Since linear regression can be easily computed, it is simple to interpret and can be used as a simple baseline to compare against more complicated non-linear models like LSTM; if a non-linear model is unable to outperform a linear baseline, then the added complexity of the model is hard to justify. It is currently the least useful model in the task, given its comparatively poor performance in the result section, which highlights the importance of the non-linear regime varying dynamics (e.g., sharp seasonal onset) that are typical of meningitis outbreak time series.

Autoregressive Integrated Moving Average (ARIMA)

In the field of time series forecasting, ARIMA is a popular statistical model comprising three components: autoregression (AR), dif-

ferencing (I) and moving average (MA) [32]. It is especially designed for univariate time series forecasting, where forecasting future series values is based on past observations, and can be used to capture trend and seasonality in the form of the (p, d, q) parameters [33]. Only historical data and a few parameters are needed for the ARIMA method, and it can manage with non-stationary data by differencing [34]. It is most applicable to short-term forecasting in relatively stationary systems where the historical trends are expected to persist [35]. For this study, the order of the ARIMA was determined with the use of the Python auto_arima routine and the result obtained was ARIMA (1,0,0) as the best fitting order for the Zamfara State series.

Long Short-Term Memory (LSTM)

The LSTM network is a variant of the RNN which is specifically designed to learn from sequential data, and to avoid vanishing gradients problem of traditional RNNs used on long sequences [36,37]. An LSTM unit has a cell state that is passed across the time steps, and the three gates in LSTM -forget gate, input gate, and output gate -determine what information to forget, to learn, and to output at every time step. The computations of the gates with the current input x_t, the previous hidden state h_{t-1}, and the previous cell state c_{t-1} are:

$$f_t = \sigma(W^f x_t + w^f h_{t-1} + b^f) \quad (1)$$

$$i_t = \sigma(W_i x_t + w_i h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma(W_o x_t + w_o h_{t-1} + b_0) \quad (3)$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tanh(Wcx_t + wch_{t-1} + bc) \quad (4)$$

$$h_t = o_t \otimes \tanh(c_t) \quad (5)$$

where f_t, i_t, and o_t denote the forget-, input-, and output-gate activation vectors respectively; $\sigma(\cdot)$ is the logistic sigmoid function, $\sigma(z) = 1/(1 + e^{-z})$, which maps its input to the range (0, 1) and thereby determines the proportion of each information component that is retained; $\otimes$ denotes element-wise multiplication; W and w denote the input and recurrent weight matrices respectively; and b denotes the corresponding bias vector for each gate [36,37]. The hyperparameters of the conventional LSTM used in this study -number of neurons, activation function, optimiser, loss function, number of epochs, and batch size -were tuned manually through iterative experimentation rather than an automated search; the final configuration is reported in Table 2.

Table 2: Hyperparameters of the manually tuned conventional LSTM.

Neurons	Activation	Optimizer	Loss	Epochs	Batch Size
118	ReLU	Adam	MSE	20	32

Particle Swarm Optimization (PSO)

PSO is an iterative metaheuristic inspired by the social behaviour of bird flocks and fish schools [38] that is based on the population. The particles are randomly placed into the search space with random velocities and velocities are initialized to a swarm of particles, each of which is a possible solution. The fitness of each particle is checked with the optimisation target, while each particle keeps an eye on the best-known position it has achieved (personal best), and the best-known position among all the particles in the swarm (global best). In each iteration a particle's velocity is modified based on the previous velocity, the difference between the current particle position and the personal best position, and the difference between the current particle position and the global best position, all scaled by an inertia term and cognitive and social acceleration terms, respectively, and then the particle position is updated using the new velocity [39]. The process continues until either the maximum number of iterations or convergence of the global best fitness is reached [40].

Genetic Algorithm (GA)

GAs are adaptive heuristic search algorithms that mimic the processes of natural selection and genetics and are applied to optimisation and search problems by evolving a set of candidate solutions (called chromosomes) over several generations by performing selection, crossover and mutation [41]. The algorithm starts with a population of candidate solutions that are randomly generated and then they are tested by a fitness function which measures their performance based on the optimisation objective. Using fitness scores, the algorithm chooses the individuals to be parents to the next generation, usually using roulette-wheel selection or tournament selection. A randomly selected set of parents goes through a process called "crossover" (recombination) in which portions of two parent solutions are mixed together to create offspring that mimic genetic recombination. Random mutations are added to a portion of the offspring to maintain the diversity of the population and prevent the population from converging on sub-optimal solutions. The new generation of offspring takes the place of some or all of the existing population and the cycle repeats from the fitness evaluation step until some stop criterion (usually a maximum number of generations or a good fitness) is reached [42].

Proposed Hybrid Models

This paper proposes and evaluates two hybrid models, one is based on an LSTM forecasting backbone and the other is based on a metaheuristic hyperparameter search procedure, as shown in Figure 1.

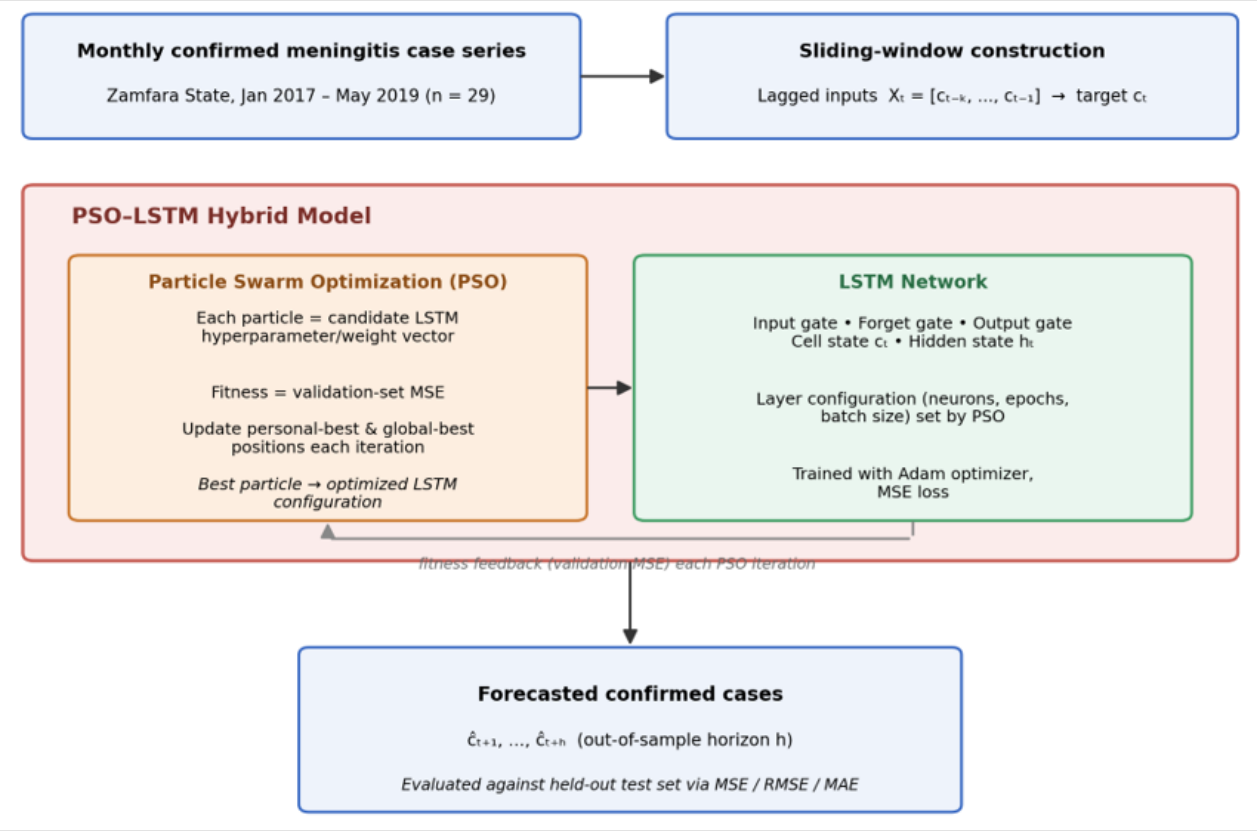

Figure 1: Architecture of the proposed PSO-LSTM forecasting pipeline: monthly Zamfara State case data are converted into lagged input windows, the LSTM's hyperparameters/weights are optimised by PSO using validation-set MSE as the fitness function, and the optimised network produces out-of-sample forecasts. GA-LSTM follows the same overall architecture, substituting a genetic algorithm for PSO as the search procedure.

Particle Swarm Optimization-Long Short-Term Memory (PSO-LSTM)

The PSO-LSTM is a hybrid model, which integrates the advantages of PSO and LSTM, respectively. The fitness value of each particle indicates the average mean squared error (MSE) loss between the predictions of the LSTM and the true value on the validation set, with each particle corresponding to a different set of hyperparameters and/or weights for the LSTM [43-46]. The particles change their velocity and positions according to their own best and the global best positions of the swarm and continue to search for the particle configuration that results in the smallest validation MSE, iteratively. After the stopping criterion is reached, the best-performing configuration is selected, and the final LSTM is trained with it and then applied to the out-of-samples forecasting. The same simulation was repeated five times, and the hyperparameter settings of the PSO-generated models were slightly different across the five replications but did not surpass the predictive accuracy of manually tuned conventional LSTM. The best PSO-LSTM configuration from these repetitions is reported as in Table 3. The parameter configuration for the PSO are swarm size = 30, iterations = 50, initial inertia weight = 0.9, final inertia weight = 0.4, c1 = 2.0, and c2 = 2.0

Table 3: Hyperparameters of the manually tuned conventional LSTM.

Neurons	Activation	Optimizer	Loss	Epochs	Batch Size
45	ReLU	Adam	MSE	35	16

Genetic Algorithm-Long Short-Term Memory (GA-LSTM)

The overall architecture of GA-LSTM is similar to that of PSO-LSTM (Figure 1), with the difference being that a genetic algorithm is used in place of the swarm-based search used in PSO-LSTM: candidate LSTM hyperparameter sets are formulated as chromosomes, tested using the MSE of the validation set, and selected, crossed, and mutated across generations. The simulation was repeated five times, and the hyperparameters configurations generated by GA were different every time and did not surpass the prediction accuracy of the conventional LSTM on this dataset. The best GA-LSTM configuration obtained is given in Table 4.

Table 4: Best GA-optimised hyperparameters for GA-LSTM.

Neurons	Activation	Optimizer	Loss	Epochs	Batch Size
45	ReLU	Adam	MSE	20	16

GA Configuration: Population size = 30, Generations = 50, Crossover rate = 0.80, Mutation rate = 0.10. The code for both PSO-LSTM and GA-LSTM optimisation is provided following the method described in [47] and readers are referred to [48] for a general treatment of hyperparameter optimisation of machine learning models, which presents other approaches – Grid Search, Random Search, Hyperband and Bayesian Optimisation with Gaussian Process or Tree-structured Parzen Estimator methods.

Input Window (Lag) Selection

In the Zamfara State series, there are only 29 monthly observations, so the construction of the exogenous variables used forward-looking multivariate feature selection was not performed, but instead a fixed sliding window of lagged monthly case counts was used as predictors of the following month's count. This is in line with the actual data set utilized in this study, which, despite the incongruous claim in an earlier version, consists solely of the monthly numbers of confirmed cases, and not of demographic, weather or other exogenous factors. The window length was determined by visual examination of the series' auto-correlation structure: the authors should specify the actual window length and preferably show the autocorrelation/partial-autocorrelation plot that led them to this choice. All models were programmed in Python 3.7.2 with Spyder Integrated Development Environment on a 2.40 GHz Intel Core i7 computer with Windows 11 operating system.

Dataset Collection and Preprocessing

The study relies on monthly confirmed case count data of meningitis cases recorded from the Nigeria Centre for Disease Control (NCDC) between January 2017 and May 2019 from all 37 states of Nigeria (including the Federal Capital Territory). The data set has 37 rows (states) and 29 columns (monthly time points). The outbreak series (monthly number of laboratories confirmed meningitis cases) was generated for each state. The univariate series for Zamfara State is a series of 29 monthly observations as detailed modelling and demonstration was conducted in this State.

Data Cleaning and Missing Values

The data used was noisy and had missing values. Imputation was used to fill in missing values and records containing too little information were excluded in order to maintain data quality.

Normalisation

The value of case count was rescaled between 0 and 1 by using the Min-Max scaling method before training the model. Min-Max scaling rather than standardisation (zero mean, unit variance) was chosen, since the output activation of the LSTM has a bounded range, and the same applies to the targets that are min-max scaled; it is a strictly monotonic transformation, meaning that relative comparisons between monthly values of cases do not change after rescaling.

Model Training and Validation

The Zamfara State series (29 monthly observations) was divided into an 80/20 training/held-out test set. To prevent overfitting and to help gauge generalisability in hyperparameter search, 10-fold cross validation was performed on the training partition, we note explicitly (as a limitation) that 10-fold cross validation on approximately 23 observations results in folds of 2–3 observations each, which provides a weak basis for hyperparameter selection, and this limitation should be taken into account when interpreting the results of the PSO-LSTM and GA-LSTM. The mean squared error (MSE) loss function and the Adam optimizer were used to train all LSTM-based models (conventional LSTM, PSO-LSTM, GA-LSTM) with hyperparameters that are listed in Tables 2-4.

Evaluation Metrics

Three widely used metrics of regression error were calculated on the held-out test partition, to assess the performance of the models. Let A_i be the number of confirmed cases in the actual (observed) data at month i, $\hat{y}_i$ the predicted value of the model at month i, and N be the number of test observations.

Squared average error (SME), which squares the average difference between the actual and the predicted value and hence puts a heavier penalty on larger errors:

$$MSE = (1/N)\sum_{i=1^N}(A_i - \hat{y})^2 \quad (6)$$

Root Mean Squared Error (RMSE), which is the square root of MSE, reported in the same scale as the case counts:

$$RMSE = \sqrt{[(1/N)\sum_{i=1^N}(A_i - \hat{y})^2]} \quad (7)$$

Mean Absolute Error (MAE): the average value of the absolute errors between actual and predicted values:

$$MAE = \sqrt{[(1/N)\sum_{i=1^N} | A_i - \hat{y}_i |} \quad (8)$$

The lower value the better the predictive performance for all three metrics. Both RMSE and MAE are directly interpretable on the scale of the outcomes (up to approximately 46 cases per month in the training data; and the former is more sensitive to large individual errors due to the sharp, spike-like increase in cases in the course of meningitis outbreaks. All three metrics are potentially strongly affected by the performance on the few months with high counts; other scale-independent metrics like MAPE or sMAPE, and a comparison against a naïve or seasonal-naïve forecast baseline would be helpful in future work.

Results and Discussion

Model Evaluation

A comparative study was conducted between the six models (PSO-LSTM, GA-LSTM, conventional LSTM, ARIMA, linear regression, and Random Forest) in terms of their prediction performance, for the prediction of confirmed meningitis cases in Zamfara State. Table 5 shows the MSE, RMSE, and MAE calculated out-of-sample on the held-out test partition. All of the deep learning models (Conventional LSTM, GA-LSTM and PSO-LSTM) significantly outperformed the classical models (Random Forest, ARIMA, linear regression) in terms of the three metrics, with Conventional LSTM having the lowest error rate. Compared to GA-LSTM, LSTM has a 7.80% decrease in MSE, 3.97% decrease in RMSE and 4.06% decrease in MAE. Compared with PSO-LSTM, LSTM improved by 24.27%, 12.97%, and 13.83% in terms of MSE, RMSE, and MAE, respectively. Compared with the other algorithms, LSTM reduced their MSE by 77.21%, 81.06%, and 87.26% for the Random Forest, ARIMA, and linear regression algorithms respectively. The advantage of deep learning models over ARIMA and linear regression is not only in the capability of the LSTM model to maintain information across multiple time steps through its gated cell-state mechanism [36,37] but also because of the fact that LSTMs can learn optimal representations incrementally with training, which is not possible with purely linear or fixed-order autoregressive models. We do not consider this to be a proof that on this particular, very short (only 29-observations) series, automatic tuning is not better than the manual tuning in general, rather it shows that on this series the extra search performed by PSO and GA did not yield a better configuration than the manual one, probably due to the limited size of the validation set, and thus the fitness signal on which both metaheuristics rely.

Table 5: Comparative performance of all six models on the held-out test partition.

Model	MSE	RMSE	MAE
LSTM	13.711	3.703	2.436
GA-LSTM	14.871	3.856	2.539
PSO-LSTM	18.105	4.255	2.827
Random Forest	60.152	7.756	4.475
ARIMA	72.404	8.509	6.011
Linear Regression	107.648	10.375	6.484

Forecast Visualisations and Twenty-Step-Ahead Predictions

For all three models PSO-LSTM, GA-LSTM and LSTM, respectively, the predicted and actual confirmed cases count on the test partition are shown in Figures 2-5. The predicted curves are alike because the three models have very similar MSE/RMSE/MAE (Table 5); if the three error measures are not plotted exactly alike, the reader is warned that this is not a plotting error, but rather a genuine difference between the models; we note this explicitly so that the similarity is not mistaken for a plotting error, and encourage readers to check the metric differences in Table 5, which, though small in absolute terms, are consistent in direction across all three error measures. The results of the twenty-step-ahead forecasts out to the next month (June 2019) are provided for each LSTM-based model in Tables 6-8. The horizon is given in monthly step units (month 1 to month 20 after May 2019), as the underlying series is monthly. One of the most prominent characteristics of all three forecasts is that they all show a very large peak at the 7th step (30 cases for PSO-LSTM, 32 cases for GA-LSTM, 26 cases for LSTM) that exceeds the range of peaks seen in the training data of approximately 25-46 cases (Figure 5). We see this increase as evidence that the models learned and extrapolated the seasonal peak of the dry season documented in the introduction and related works sections in [11] and projected this onto the period of the year seen as the seasonality for meningitis in Nigeria (December–January).

Table 6: PSO-LSTM twenty-step-ahead forecast (monthly steps following May 2019).

Step	Forecast Month	Predicted Confirmed Cases
1	2019-06	0
2	2019-07	0
3	2019-08	0
4	2019-09	1
5	2019-10	3
6	2019-11	11
7	2019-12	30
8	2020-01	15
9	2020-02	1
10	2020-03	0
11	2020-04	0
12	2020-05	0
13	2020-06	1
14	2020-07	2
15	2020-08	8
16	2020-09	19
17	2020-10	19
18	2020-11	2
19	2020-12	0
20	2021-01	0

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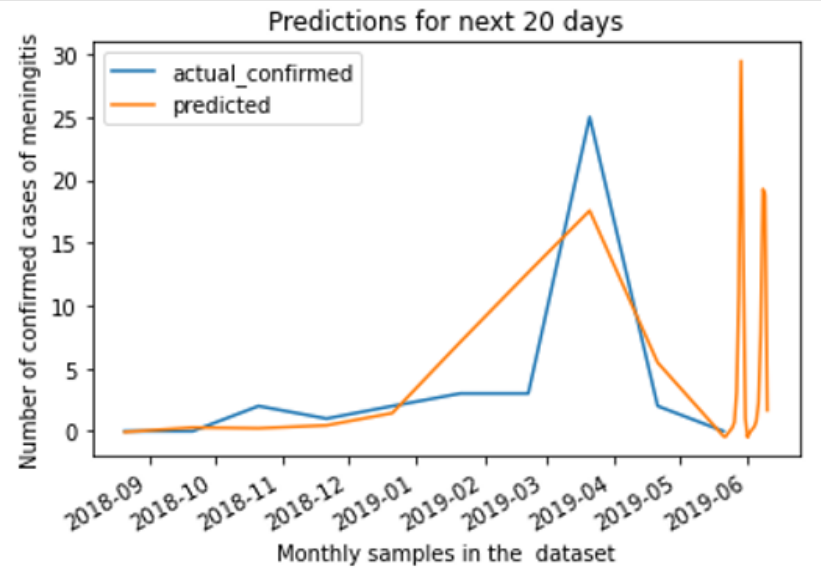

Figure 2: PSO-LSTM: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

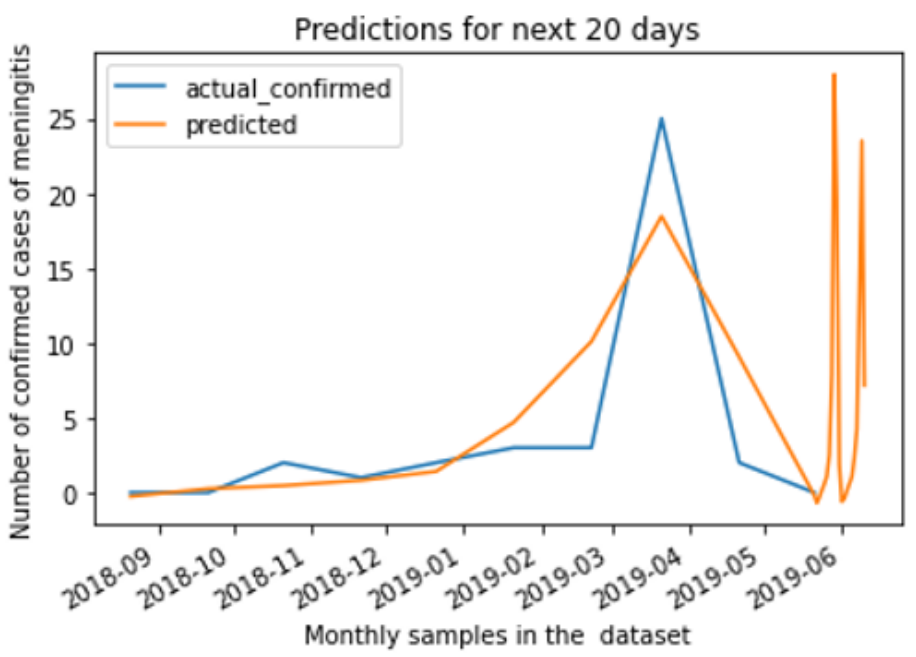

Figure 3: GA-LSTM: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

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Table 7: GA-LSTM twenty-step-ahead forecast (monthly steps following May 2019).

Step	Forecast Month	Predicted Confirmed Cases
1	2019-06	1
2	2019-07	0
3	2019-08	0
4	2019-09	1
5	2019-10	2
6	2019-11	7
7	2019-12	32
8	2020-01	23
9	2020-02	3
10	2020-03	0
11	2020-04	0
12	2020-05	1
13	2020-06	1
14	2020-07	2
15	2020-08	4
16	2020-09	7
17	2020-10	20
18	2020-11	10
19	2020-12	0
20	2021-01	0

Table 8: Conventional LSTM twenty-step-ahead forecast (monthly steps following May 2019).

Step	Forecast Month	Predicted Confirmed Cases
1	2019-06	0
2	2019-07	0
3	2019-08	0
4	2019-09	1
5	2019-10	2
6	2019-11	6
7	2019-12	26
8	2020-01	19
9	2020-02	2
10	2020-03	0
11	2020-04	0
12	2020-05	0
13	2020-06	1
14	2020-07	2
15	2020-08	3
16	2020-09	8
17	2020-10	21
18	2020-11	11
19	2020-12	0
20	2021-01	0

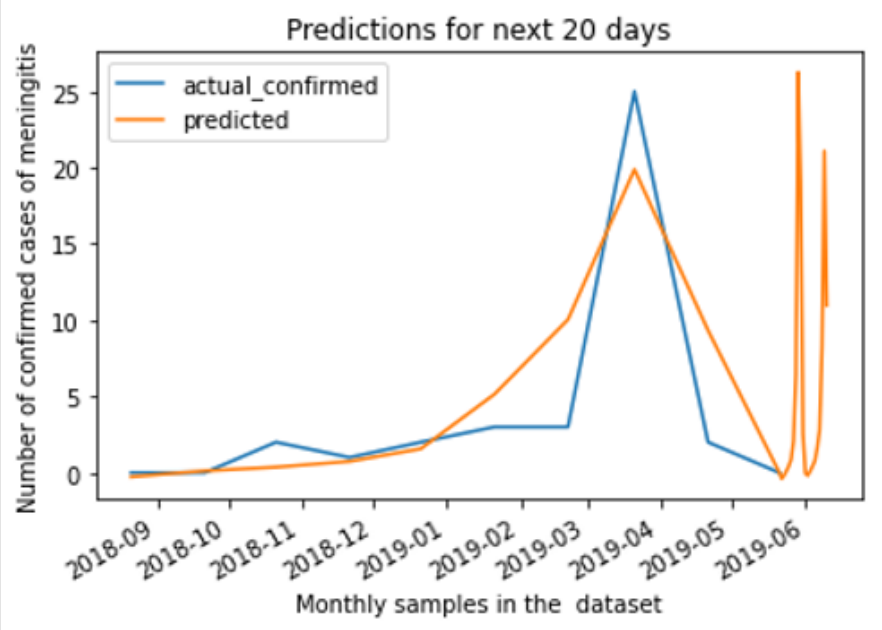

Figure 4: Conventional LSTM: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

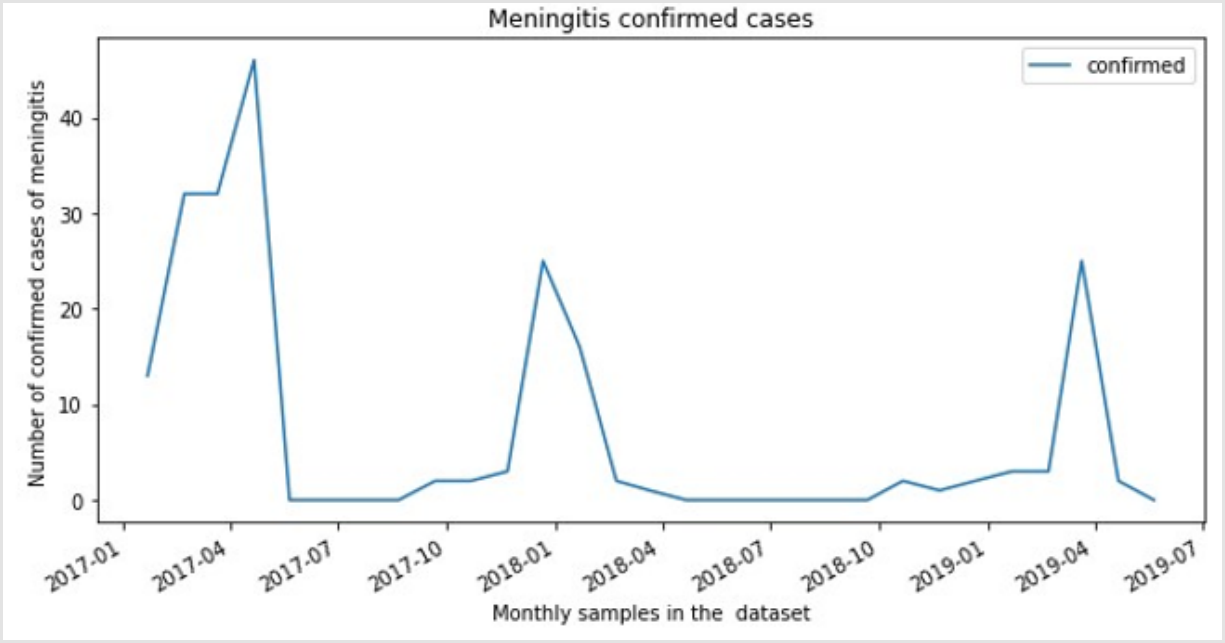

Figure 5: Monthly confirmed meningitis case counts in Zamfara State, January 2017 to May 2019 (29 monthly observations).

Classical Baseline Models: ARIMA, Linear Regression, and Random Forest

Figure 6 plots the ARIMA (1,0,0) forecast of the test-partition values. The forecast looks very close to a straight horizontal line at 4-5 cases and fails to capture the sharp seasonal peaks as seen in the actual series, which is in keeping with the limited representation capability of the ARIMA (1,0,0) specification using a first-order autoregressive term alone, and is evident quantitatively in the comparatively high MSE, RMSE, and MAE in Table 5. This qualitative failure to track peaks is exactly the kind of information that can be under-communicated by a completely numeric error measure, which is why we are providing the visualisation in addition to the error measures, and not as a substitute. As seen in (Figures 7,8), linear regression and Random Forest follow a relatively flat path through the test data and also do not pick up on the sharp peaks, as linear regression could not capture non-linear dynamics, and as a piecewise-constant 'averaging' method, Random Forest would under-predict extreme values not well represented in the training set of this size. While the error of Random Forest is considerably smaller than either of the purely linear/autoregressive models (ARIMA, linear regression), it is still significantly higher than all three of the LSTM-based models (Table 5), indicating some level of non-linear structure being captured by the Random Forest model, but which these two linear models do not.

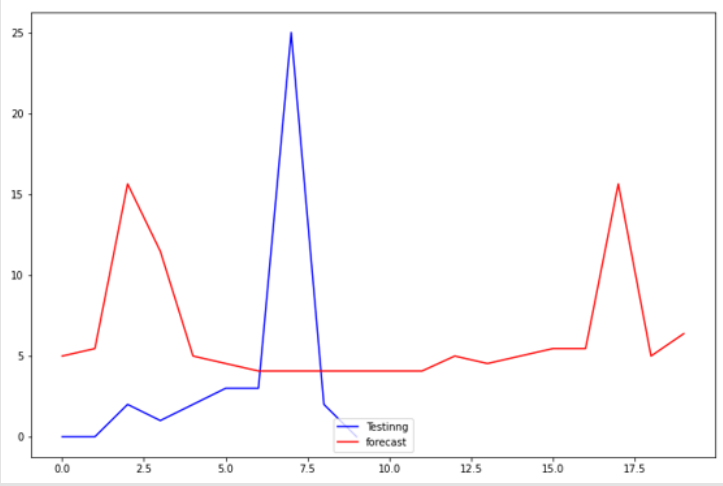

Figure 6: ARIMA: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

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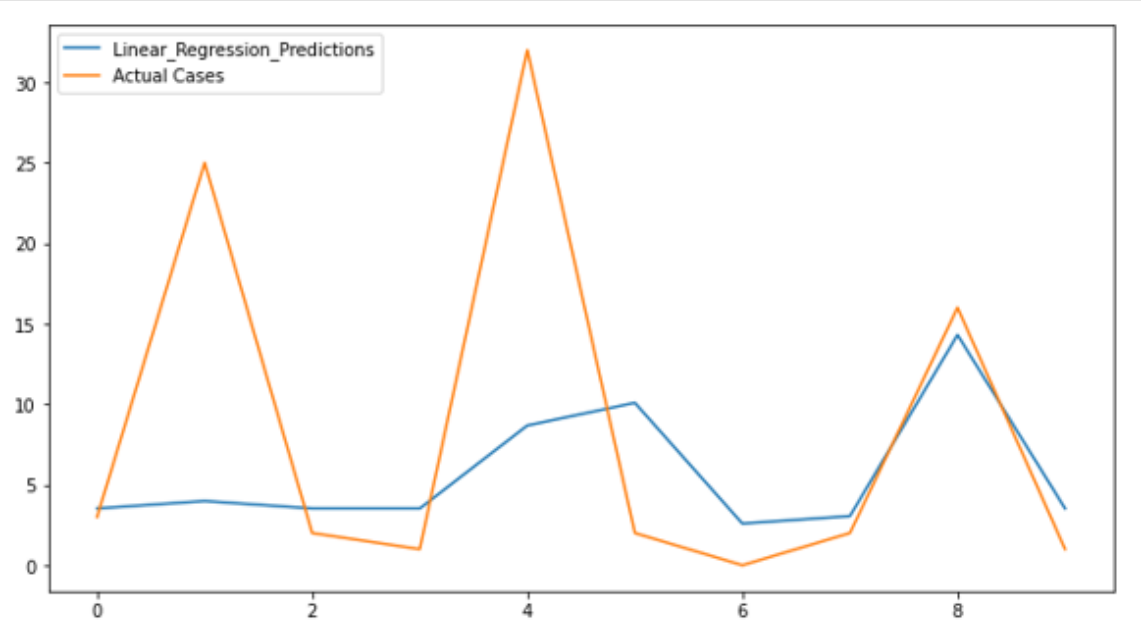

Figure 7: Linear Regression: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

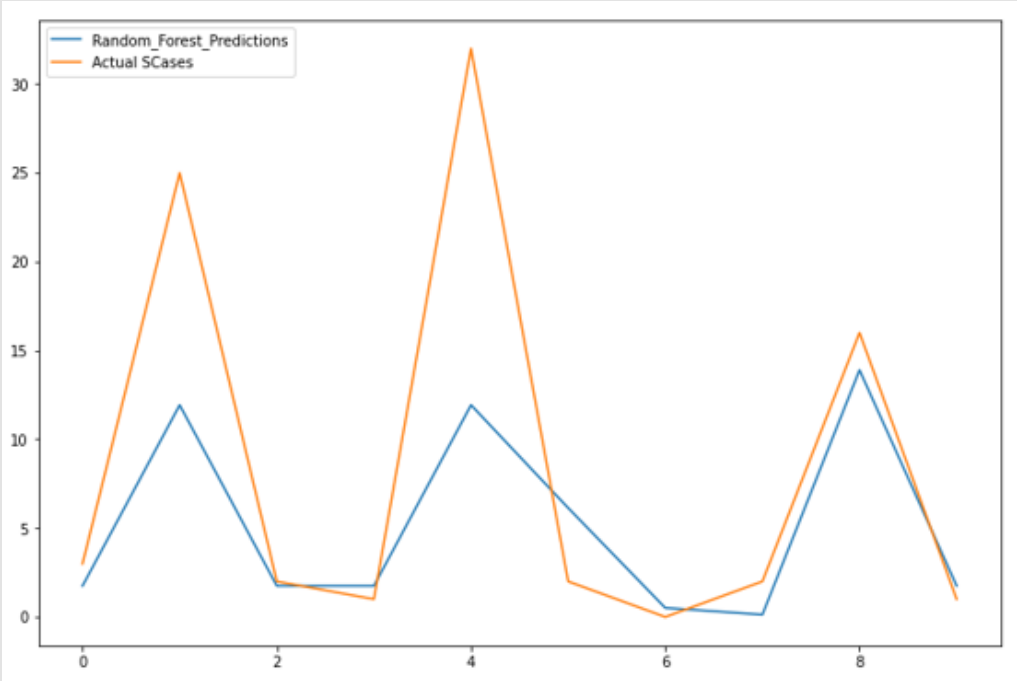

Figure 8: Random Forest: predicted vs. actual confirmed meningitis cases, Zamfara State test partition.

Conclusion

This study proposed and evaluated six techniques: PSO-LSTM, GA-LSTM, conventional LSTM, ARIMA, linear regression, and Random Forest to predict the number of confirmed cases of meningitis in the study area, Zamfara State, Nigeria from 2017 to 2019 based on monthly data obtained from the Nigeria Centre for Disease Control (NCDC). Three error metrics were used and the manually tuned conventional LSTM achieved better performance than the two-metaheuristic optimised LSTM based models (GA-LSTM and PSO-LSTM) and the statistical and regression-based models (ARIMA, linear regression, and Random Forest). All three LSTM variants significantly outperformed ARIMA, linear regression and Random Forest on all metrics, showing that deep sequence models can learn a meaningful short term forecasting signal from this surveillance series even at a very small sample size. This work serves as a proof-of-concept meningitis outbreak forecasting pipeline; with further validation, as described below, it could be used to design an early-warning tool to help health decision-making officials predict an imminent outbreak in a specific state, but we do not claim to have designed the current pipeline as an early-warning tool because it has not been deployed, tested with users, or evaluated with respect to the decisions it could inform.

Limitations

- Sample size: With only 29 monthly observations for the Zamfara State series, there were about 23 training observations and 6 test observations after splitting the data into 80/20. This is a small sample, for 45-135 LSTM neurons, to train deep learning models, and, as 10-fold cross-validation is performed on the approximate number of 23 observations, the level of support for hyperparameter selection is weak. The results should be read as a proof of concept demonstration and not as a comprehensive evaluation.

- Single-state evaluation: The primary analysis was based on a single state (Zamfara State) and the generalisation of the approach to any Nigerian state is not yet evidenced.

- Forecast horizon and validation: The validations (Tables 6-8) extend beyond the observed period of validation and the forecast peak at step 7 is a plausible seasonal extrapolation, but has not yet been validated against true observations in the future.

- Our initial hypothesis was that metaheuristic optimisation would yield an improved performance for the conventional LSTM in terms of its prediction accuracy. Even though this was not the case, it is unclear whether this is due to (1) a genuine cap on the performance of the conventional LSTM on this dataset, (2) an inadequate validation signal, or (3) inaccurate search parameters for PSO/GA.

- The models do not include exogenous variables: In addition to the lagged case counts, climatic, demographic, and health-system variables that are plausible and might affect the transmission of meningitis were not included.

Future Work

Future work should include:

(i) Inclusion of additional states to test for generalisability, including at least one additional high and low burden state;

(ii) Inclusion of climatic and other exogenous predictive variables to create a more robust predictive model, using a wide range of data sources for this;

(iii) A longer surveillance series to enable more reliable deep learning model training and cross-validation, either from NCDC's weekly reporting data (when available) or through pooling across states with state fixed effects;

(iv) The use of a rolling-origin (walk-forward) validation approach, or a combination of approaches, rather than a single fixed train/test split;

(v) Peporting of all PSO and GA search parameters and a formal test of the differences between models; and

(vi) Balidation of the twenty step-ahead forecasts against actual NCDC observations as they become available.

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Data Availability Statement

The dataset used in this study is available from the corresponding author upon reasonable request.

Declarations

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval: Not applicable.

Consent to participate: Not applicable.

Consent for publication: Yes.

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