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Research Article

Research on an intelligent assessment method for the physical health of preschool children based on the Artificial Neural Network (ANN) model

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ABSTRACT

This study aims to use the BP neural network model to predict the monthly total number of reported symptoms in preschool children, thereby achieving early warning for the total number of cases in the current month. By analyzing the training results of the neural network and the fitting of the model, the feasibility and effectiveness of the BP neural network in monitoring the physical health of preschool children are validated. The predictive model is of great significance for the prevention of infectious diseases in a border region of a certain province, providing important information for the local incidence situation. The research results indicate that the established BP neural network model demonstrates good accuracy and practicality in predicting the monthly total number of reported symptoms in preschool children's physical health.

Keywords: Preschool children; physical health monitoring; BP neural network

1. Introduction

The health status of preschool children has a significant impact on their comprehensive development and future life; therefore, effective monitoring and assessment are crucial to ensure their healthy growth[1]. Traditional methods of health assessment rely on comprehensive physical examinations conducted by doctors or specialized medical institutions, which, while accurate, are time-consuming and challenging to apply in large-scale child populations[2]. With the rapid development of information technology and artificial intelligence, computer-assisted assessment methods have emerged. However, limitations persist in data processing and result interpretation. In recent years, the rise of artificial intelligence and machine learning technologies has brought new possibilities for the assessment of the health of preschool children. Artificial Neural Networks (ANN), as a vital artificial intelligence method, have garnered widespread attention[3]. Neural network models possess robust nonlinear fitting capabilities and adaptive learning features. By learning from extensive data on children's health, they can automatically capture complex relationships and patterns, facilitating accurate assessment and prediction of children's health status[4]. This emerging intelligent assessment method provides a more efficient and convenient approach to the health monitoring of large-scale child populations. Moreover, international studies have confirmed the effectiveness of neural networks in

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predicting Body Mass Index (BMI) and monitoring growth and development in children, demonstrating significant potential for widespread application[5].

In the field of health assessment, neural networks have achieved remarkable results, including predictions and diagnoses related to cardiovascular diseases and diabetes. Among them, Back-Propagation Network (BP neural network) is a multi-layer feedforward network trained using the error backpropagation algorithm. It possesses strengths such as strong adaptability, high fault tolerance, and robust organizational capabilities. In the prediction of diseases, BP neural networks exhibit broad application potential and can be applied to monitor the health of preschool children[6]. However, despite the encouraging achievements of neural network-based health intelligent assessment methods, some challenges remain. Issues related to data quality and sample size are significant challenges. Establishing effective neural network models requires a substantial amount of high-quality training data, and obtaining and cleaning data may sometimes be difficult[7]. Additionally, the complexity of neural network models poses limitations in terms of interpretability compared to traditional methods, especially in the field of children's health, where further research is needed.

Therefore, this paper aims to use the BP neural network prediction model to monitor the health of preschool children. While accurately predicting the number of disease symptoms, it is essential to address the challenge of timely reflecting the overall health status of preschool children, enabling disease control centers to proactively implement preventive measures and warnings.

2. Review of the literature

2.1. The historical development of physical health assessment methods for preschool children

The initial assessment of physical health in preschool-age children primarily relied on comprehensive physical examinations and physiological function evaluations conducted by doctors or specialized medical institutions. While this approach was relatively accurate, it demanded significant manpower and resources, limiting its applicability in large-scale child populations. With the advancement of information technology, computer-assisted assessment methods began to emerge. For instance, computers were employed to measure children's height, weight, head circumference, and other data to assist in evaluating normal growth and development. This approach improved assessment efficiency but still faced limitations in data processing and result interpretation.

In recent years, with the proliferation of artificial intelligence and machine learning technologies, the evaluation of physical health in preschool children has entered a new era of intelligence. Among these, neural network models, as a significant artificial intelligence method, have garnered considerable attention from researchers. By learning from extensive datasets of children's physical health, neural network models can automatically capture intricate relationships and patterns within the data, enabling accurate assessment and prediction of children's physical health status[8].

In addition to neural network-based methods, several other intelligent assessment approaches have emerged, such as machine learning models like Support Vector Machine (SVM) and Decision Trees. These methods have shown certain advantages in evaluating the physical health of preschool children. However, in comparison, neural network models, owing to their robust non-linear fitting capability and adaptive learning characteristics, are better equipped to handle complex and ever-evolving physical health issues.

2.2. Advantages and disadvantages of traditional assessment methods

2.2.1. Advantages

(1) Professional: Traditional evaluation methods are typically conducted by doctors or experienced

medical professionals equipped with extensive knowledge and expertise. They can perform a comprehensive and meticulous assessment of the physical health status of preschool children, encompassing aspects such as growth and development, physiological function, and more.

(2) High Accuracy: Traditional assessment methods rely on physical examinations and medical measurements, providing highly precise data to detect potential health issues in children. This accuracy aids in early intervention to prevent further deterioration of any diseases.

(3) Comprehensive: Traditional assessment methods take into account various physical indicators and physiological parameters, allowing for a comprehensive evaluation of the physical health of preschool children. This approach facilitates a holistic understanding of their health status[9].

2.2.2. Disadvantages

(1) Time-consuming and Laborious: Traditional evaluation methods necessitate physical examinations and measurements by doctors or professional medical personnel, which can be time-consuming and labor-intensive, especially when dealing with large groups of children, leading to reduced efficiency.

(2) Subjectivity: Traditional evaluation methods are subject to the influence of a doctor's personal experience and subjective judgment to some extent. This subjectivity may introduce errors and result in less objective and consistent evaluation outcomes.

(3) Data Processing Challenges: The data produced by traditional evaluation methods tend to be more complex, involving multiple indicators and parameters. This complexity makes it difficult to process and analyze a large volume of data, thereby limiting the comprehensive utilization of the information.

(4) Lack of Real-time Monitoring: Traditional evaluation methods often require children to visit medical facilities for examinations, making it challenging to monitor their physical health in real-time, especially during daily life and emergencies.

(5) Limited Interpretability: While traditional evaluation methods can deliver evaluation results, the interpretation and cause analysis of these results may be limited. They might lack in-depth interpretation and visual representation of the evaluation process.

2.3. Overview of the application of neural networks in physical health assessment

The application of neural networks in the assessment of physical health primarily centers on harnessing their robust non-linear fitting capabilities and adaptive learning characteristics to process extensive datasets from preschool-age children. This empowers accurate evaluation and prediction of the physical health status of these children. Neural network models enable a comprehensive and intelligent assessment of various indicators, including physical growth and development, physiological functions, and health risks. This approach offers a more scientific and efficient means of managing and intervening in the health of preschool-age children while also driving innovative breakthroughs and advancements in the field of physical health research and development for this age group[10].

2.4. Research status of ANN-based body health intelligent assessment method

The use of Artificial Neural Networks (ANN) in intelligent health assessment for physical well-being is a burgeoning and highly esteemed research field. Presently, both domestic and international scholars have displayed growing interest in this area, encompassing assessments of children across various age groups and diverse physical health indicators.

On the international front, several studies have confirmed the effectiveness of ANN in appraising children's physical health. For instance, researchers have employed ANN models to predict and categorize children's Body Mass Index (BMI) with encouraging results. Furthermore, some scholars have applied ANN to forecast children's growth and development, creating intelligent assessment models through the analysis of extensive growth data. This approach has effectively aided in monitoring children's growth and development[11–14].

In China, researchers have also delved into comprehensive investigations regarding ANN-based intelligent health assessment methods. Some of these studies have concentrated on the physiological evaluation of children, encompassing aspects such as cardiorespiratory fitness and physical performance. Through the collection of physiological data from children and the development of ANN models, these studies have successfully predicted and classified children's physiological functional levels. Furthermore, notable progress has been made in predicting chronic diseases in children. By integrating clinical data and physiological indicators and leveraging ANN models, researchers have effectively assessed and foreseen the risk of chronic diseases in children, offering substantial support for early intervention[15,21–23].

Despite achieving promising results with ANN-based intelligent health assessment methods both domestically and internationally, there are several challenges to contend with. Notably, the quality of data and sample size plays a significant role. The development of effective ANN models necessitates a substantial amount of high-quality training data, which can sometimes be challenging to obtain and clean. Additionally, model interpretability remains a crucial concern. Due to the intricacies of ANN models, their ability to explain assessment results may not be as robust as that of traditional methods, potentially limiting their applicability in the realm of children's physical health[24,25].

3. Data preprocessing

The focus of this study is to predict the total number of reported symptoms each month, with a primary emphasis on investigating the impact of the reported quantities of other symptoms on the overall total. Generally, a single patient's symptom record includes several symptoms, such as fever, headache, cough, etc., and is considered as one record for the total count. All the data studied in this paper were extracted through the Border Symptom Monitoring and Early Warning System, ensuring the authenticity and reliability of the data. This early warning system mainly collects real-time symptom data reported by all medical institutions in a specific region of China. Due to the variability in the units of input data, with some ranges being quite large, the convergence speed of the neural network is slow, and the training time is prolonged. Therefore, the data is normalized using Equation (1)[7,11] to ensure that the sample data falls within the range of [0, 1].

$$x_j = \frac{x_i - x_{min}}{x_{max}} \tag{1}$$

Among them, x_i represents the data to be normalized, x_{min} represents the minimum value of the data to be normalized, x_{max} represents the maximum value of the data to be normalized, and x_j represents the normalized data. Some symptoms have very few reported cases each month, with minimal impact on the overall count. Only the counts of five symptoms with relatively higher frequencies, namely fever, headache, cough, abdominal pain, and sore throat, are considered. It is sufficient to know the monthly total reported counts for these five symptoms to predict the overall symptom reports for the month. The processed data is shown in **Table 1**.

The following is the normalized data table for monthly symptom reports in a border province from January to December 2022:

Table 1. The normalized data for monthly symptom reports.

Month	Fever	Headache	Cough	Abdominal pain	Sore throat	Total records
01	0.3907	0.0869	0.1726	0	0.0478	0.1089
02	0	0	0	0.0374	0	0
03	0.2648	0.2678	0.2266	0.3526	0.1440	0.2617
04	0.1398	0.1689	0.2052	0.3540	0.1273	0.2546
05	0.1602	0.2494	0.1767	0.5045	0.1306	0.3080
06	0.0889	0.1808	0.0245	0.4439	0.0911	0.1994
07	0.2077	0.4707	0.1139	0.6793	0.1769	0.2879
08	0.1317	0.5136	0.0922	0.7007	0.1233	0.2487
09	0.0622	0.4096	0.2091	0.6715	0.1151	0.3003
10	0.4276	0.5682	0.3153	0.7162	0.2205	0.4373
11	1	1	1	1	1	1
12	0.6065	0.5825	0.4720	0.7244	0.3473	0.5466

4. BP prediction model

4.1. BP neural network learning algorithm principles

The BP neural network algorithm, as a supervised learning process, involves iteratively adjusting the weights and thresholds of network connections based on known input-output sample data to make the network's output closer to the desired output. For the entire neural network, one learning process consists of two subprocesses[12,26]: the forward propagation of input data and the backward propagation of errors. The classic BP network structure is illustrated in **Figure 1**.

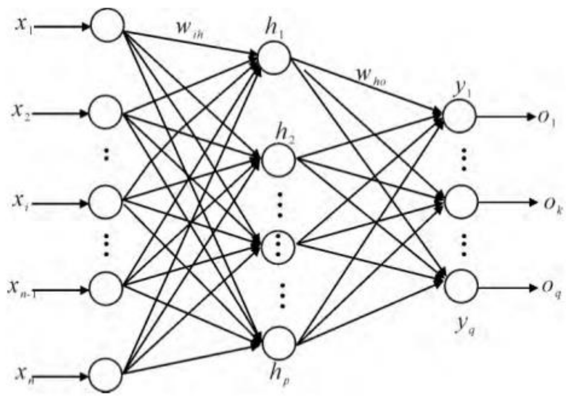

Figure 1. The classic BP network structure

From **Figure 1**, it can be observed that the input layer has n neurons, the hidden layer has p neurons, and the output layer has q neurons. Define the following variables:

Input vector:

Hidden layer input vector: $x = (x_1, x_2 \ldots\ldots, x_n)$

Hidden layer output vector: $h_i = (h_{i1}, h_{i2} \ldots\ldots, h_{in})$

Output layer input vector: $y_i = (y_{i1}, y_{i2} \ldots\ldots, y_{in})$

Output layer output vector: $y_o = (y_{o1}, y_{o2} \ldots\ldots, y_{on})$

Expected output vector: $d_o = (d_1, d_2 \ldots\ldots, d_n)$

Connection weights between the input layer and the hidden layer: ω_{ih}

Connection weights between the hidden layer and the output layer: ω_{io}

Thresholds for each neuron in the hidden layer: b_h

Thresholds for each neuron in the output layer: b_o

Number of sample data: $k = 1,2,\ldots\ldots,m$

Step 1: Initialization—Assign a random number from-1to1 to each connection weight, set the error function *e* define the precision value for computation as ε and set the maximum number of learning iterations as *M*.

Step 2: Randomly select the *k*-th input sample and its corresponding expected output.

$$x(k) = (x_1(k), x_2(k)\ldots\ldots, x_n(k))$$
$$d_0(k) = (d_1(k), d_2(k)\ldots\ldots, d_n(k))$$

Step 3: Calculate the input and output for each neuron in the hidden layer.

$$\mathrm{hi}_{\hbar}(k) = \sum_{i=1}^{n} \omega i\hbar xi(k) - b_{\hbar} \quad \hbar = 1,2,\ldots..p$$

$$\mathrm{ho}_{\hbar}(k) = f(\hbar i_{\hbar}(k)) \qquad o = 1,2,\ldots..p$$

$$\mathrm{yi}_o \text{（}k\text{）} = f(yi_o(k)) \quad o = 1,2,\ldots..p$$

Step 4: Compare the network's expected output with the actual output and obtain the partial derivatives $\delta_o(k)$ of the error function with respect to each neuron in the output layer[13].

$$\frac{\partial e}{\partial \omega_{\hbar o}} = \frac{\partial e}{\partial yi_o}\frac{\partial \mathrm{yi}_o}{\partial \omega_{\hbar o}} = -\delta(k)\hbar o_{\hbar}(k)$$

$$\frac{\partial \mathrm{yi}_o(k)}{\partial \omega_{\hbar o}} = \frac{\partial(\sum_{\hbar}^{p} \omega_{\hbar o}\hbar o_{\hbar}(k) - b_o)}{\partial \omega_{\hbar o}} = \hbar o_{\hbar}(k)$$

Step 5: Utilize the connection weights from the hidden layer to the output layer, the $\delta_o(k)$ values for the output layer, and the output from the hidden layer to compute the partial derivatives $\delta_h(k)$ of the error function with respect to each neuron in the hidden layer.

$$\frac{\partial e}{\partial \hbar i_{\hbar}(k)} = \frac{\partial(\frac{1}{2}\sum_{o=1}^{q}(d_o(k)\text{-}\mathrm{yo}_o(k))^2)}{\partial \hbar o_{\hbar}(k)}\frac{\partial \hbar o_{\hbar}(k)}{\partial \hbar i_{\hbar}(k)} = \frac{\partial(\frac{1}{2}\sum_{o=1}^{q}((d_o(k)\text{-}\mathrm{f}(\sum_{\hbar=1}^{p}\omega_{\mathrm{ho}}\hbar o_{\hbar}(k)\text{-}\mathrm{b}_o))^2)}{\partial \hbar o_{\hbar}(k)}\frac{\partial \hbar o_{\hbar}(k)}{\partial \hbar i_{\hbar}(k)}$$
$$= -(\sum_{o=1}^{q}\delta_o(k)\omega_{\hbar o})f(\hbar i_{\hbar}(k)) - \delta_{\hbar}(k)$$

Step 6: Adjust the connection weights $\omega_{\mathrm{ho}}(k)$ between the hidden layer and the output layer by comparing the $\omega_{\mathrm{ho}}(k)$ values for each neuron in the output layer with the output from each neuron in the hidden layer[14].

$$\Delta W_{\hbar o} = -\mu\frac{\partial e}{\partial w_{\hbar o}} = \mu\partial_o(k)\hbar o_{\hbar}(k)$$

$$w_{\hbar o}^{N+1} = w_{\hbar o}^{N} + \eta\delta_o(k)\hbar o_{\hbar}(k)$$

Step 7: Compare the $\delta_{\mathrm{h}}(k)$ for each neuron in the hidden layer with the input correction connection weights for each neuron in the input layer.

$$\Delta\omega_{\mathrm{ih}}(k) = -\mu\frac{\partial e}{\partial\omega_{\mathrm{ih}}} = -\mu\frac{\partial e}{\partial \mathrm{hi}_{h}(k)}\frac{\partial \mathrm{hi}_{h}(k)}{\partial\omega_{\mathrm{ih}}} = \delta_{h}(k)\chi_i(k)$$

$$\Delta\omega_{\mathrm{ih}}(k) = -\mu\frac{\partial e}{\partial\omega_{\mathrm{ih}}} = -\mu\frac{\partial e}{\partial \mathrm{hi}_{h}(k)}\frac{\partial \mathrm{hi}_{h}(k)}{\partial\omega_{\mathrm{ih}}} = \delta_{h}(k)\chi_i(k)$$

Step 8: Calculate the global error.

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(d_o(k) - y_o(k))^2$$

Step 9: Determine whether the network error meets the preset conditions. If the error exceeds the assumed precision or the number of learning iterations surpasses the assumed maximum, terminate the algorithm. Otherwise, continue with the subsequent learning samples and their corresponding expected output results. Repeat Step 3, and proceed to the next learning iteration[15].

This step involves checking if the learning process should continue based on predefined criteria such as reaching a desired level of accuracy or staying within a specified number of learning iterations. If the conditions are met, the algorithm concludes; otherwise, it proceeds to the next iteration of learning with additional samples[16].

4.2. Algorithm establishment

In this study, a three-layer structure using the BP neural network algorithm is employed to construct a nonlinear predictive model for the total number of symptoms based on the individual counts of five symptoms. The model takes the monthly record counts of these five symptoms as inputs and predicts the total monthly symptom count as the output. The transfer function for neurons in the intermediate layer is the sigmoid hyperbolic function, and since the input vector values fall within the range of [0, 1], the transfer function for neurons in the output layer can be set as the sigmoid logarithmic function[17–20].

The built-in training function traingdx is chosen for training the network, which adapts its learning rate. Through multiple tests, the optimal prediction accuracy is achieved when the number of neurons in the hidden layer is set to 10. The training dataset comprises data from January to November 2022, while the data from December 2022 is used as the prediction dataset[27,28].

5. Experimental results and analysis

Initially, with a learning rate of 0.05, 1000 training steps, and a training target of 0.001, the network was trained using the input data

P=[0.3907,0.0869,0.1726,0,0.0478;0,0,0,0.0374,0;0.2648,0.2678,0.2266,0.3526,0.1440;0.1398,0.1689,0.2052,0.3540,0.1273;0.1602,0.2494,0.1767,0.5045,0.1306;0.0889,0.1808,0.0245,0.4439,0.0911;0.2077,0.4707,0.1139,0.6793,0.1769;0.1317,0.5136,0.0922,0.7007,0.1233;0.0622,0.4096,0.2091,0.6715,0.1151;0.4276,0.5682,0.3153,0.7162,0.2205;1,1,1,1,1]′

and the corresponding expected output data

T = [0.1089,0.2617,0.2546,0.3080,0.1994,0.2879,0.2487,0.3003,0.4373,1].

The BP network reached the expected error in the 121st step, and the training error reduction curve is illustrated in **Figure 2**. The training process took less than 1 minute.

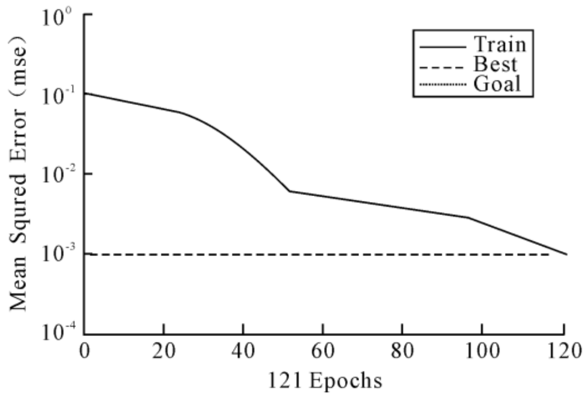

Figure 2. Neural network training error reduction curve.

Figure 3: The fitting plot of the BP neural network predicted values

y = [0.1026,0.0628,0.2481,0.2715,0.3027,0.1661,0.3205,0.2649,0.2672,0.4406,0.9499].

compared to the target output values (T = [0.1089, 0, 0.2617, 0.2546, 0.3080, 0.1994, 0.2879, 0.2487, 0.3003, 0.4373, 1]*. The asterisks (*) represent the target output values, and the solid line represents the fitted values corresponding to the BP neural network output. The vertical axis represents the normalized values. From **Figure 3**, it is evident that the fitting degree between the two is quite high.

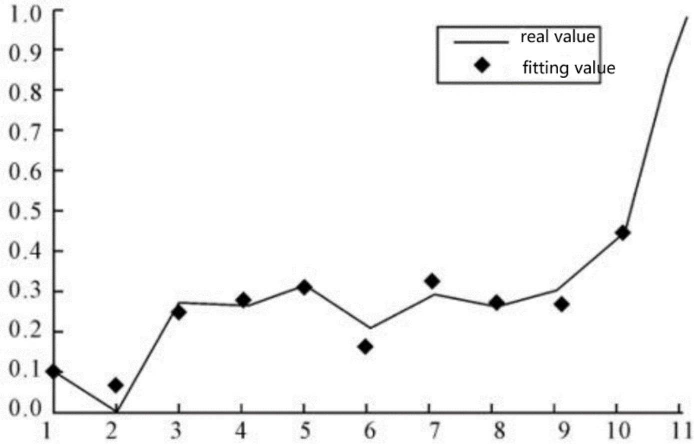

Figure 3. Comparison between BP network fitted values and target output values.

Figure 4: The error between the target output values and the fitted values of the BP neural network is shown in **Figure 4**. It can be observed that the error between the network output and the target output values is very small, indicating a satisfactory predictive result and validating the effectiveness of the BP neural network prediction.

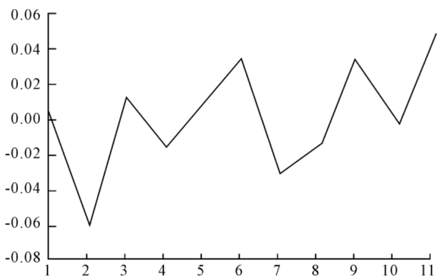

Figure 4. Error between target output values and fitted values of the BP network.

The relative errors of the network output values are presented in **Table 2**. The BP neural network model achieves a minimum relative error of 1.10% and a maximum of 7.28% in fitting the training dataset. This indicates a favorable predictive performance of the BP neural network model.

Table 2. Errors between network output values and actual values.

Month	Network Output (Converted)	Actual Value	Absolute Error	Relative Error (%)
January 2022	0.1026	13,393	13,769	376
February 2022	0.0628	12,587	12,185	402
March 2022	0.2481	16,703	17,392	689
April 2022	0.2715	17,038	17,228	190
May 2022	0.3027	17,466	18,494	1,028
June 2022	0.1661	15,422	15,917	495
July 2022	0.3205	17,702	18,017	315
August 2022	0.2649	16,945	17,087	142
September 2022	0.2672	16,978	18,312	1,334
October 2022	0.4406	20,137	21,563	1,426
November 2022	0.9499	32,867	34,916	2,049

In **Table 1** data, for the values in 2022 [0.6065,0.5825,0.4720,0.7244,0.3473]′, when inputting this set of data into the pre-trained network, the preliminary predicted value is 0.5359. After reverse normalization, the predicted value is 24,603. The absolute error between this prediction and the actual total record count of 24,157 in December 2022 is 446, with a relative error of 1.84%. The predicted value is very close to the actual value, confirming the feasibility of the BP neural network prediction model.

6. Conclusion

This paper has established an early warning model based on the BP neural network to predict the total number of preschool children affected in a given month based on the monthly reported counts of each symptom. Through experiments, the feasibility of the BP neural network prediction model in forecasting the overall health condition of preschool children, specifically the total monthly reported counts, has been confirmed[29]. The establishment of this predictive model holds significant importance for the prevention of infectious diseases in a border region of a certain province. It can provide crucial insights for predicting the incidence of diseases in the local area.

Author contributions

Conceptualization, HLand JM; methodology, HL; software, MA; validation, HL, JM and MA; formal analysis, HL; investigation, JM; resources, JM; data curation, HL; writing—original draft preparation, HL; writing—review and editing, JM; visualization, MA; supervision, JM; project administration, MA; funding acquisition, JMA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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