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Prediction Children's Gnawing Behaviour Based on Machine Learning

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Abstract: The relationship between parenting quality and children's social behaviour (e.g. gnawing) is also moderated by other variables, particularly the possible interaction between parental meta-emotional beliefs and children's temperament on children's socialisation development. This paper therefore uses machine learning to predict children's gnawing behaviour and uses the predictions to develop innovative designs for gnawing toys. This paper uses machine learning to identify and judge selection features. Machine learning includes random forest models and adaboost model (AM), and the AM is chosen to predict children's chewing behaviour through prediction performance and fitting result analysis. The paper begins with an analysis and description of the significant differences in mothers' behavioural responses and outcome measures, followed by an analysis of feature importance and prediction performance and fitting results, and finally an optimisation of the prediction model and toy design.

1. Introduction

The formation and development of children's nibbling behaviour provides a special context in which to explore parent-child interactions [1]. Child nibbling has long been a common topic of research among developmental psychologists, particularly in preschool children, who are prone to nibbling during the adjustment process from home to school [2-3]. Parental reactivity or parental beliefs are strongly associated with the development of nibbling behaviour, and there are both similarities and differences in parental responses to implicit and explicit nibbling behaviour, with both cross-culturally consistent and culturally specific responses possible [4-5]. Gnawing behaviour tends to occur during the teething period and the innovative design of gnawing toys for infants and toddlers can help parents to increase their attention to their children's milk teeth [6-7]. The innovative design of gnawing toys for infants and toddlers can help parents to pay more attention to their children's milk teeth and provide them with a new experience and care in the form of toys [8].

With the improvement of people's living standards, more and more researchers predict children's gnawing behavior based on machine learning, and have achieved good results [9]. For example, Thomas H. Weisswange et al. proposed a mixed multi label random forest model, and the multi label decision tree was used as a basic classifier to build the HML-RF model. Each basic classifier is constructed on a randomly selected label subset to take advantage of label dependency. Experimental results show that HML-RF performs better on at least six datasets, and HML-RFws has high accuracy on at least nine datasets [10]. Florian Wirthmuiller et al. used VADER based on semantics and rules to calculate polarity scores and classify emotions, overcoming the weakness of manual annotation. At the same time, they used random forests as their supervised classifiers. The results showed that HyVADRF model always provided stable results [11]. The prediction of children's gnawing behavior based on machine learning is beneficial to children's healthy development.

With the development of economy, more and more parents begin to pay attention to the problem behaviors found in children's growth, especially children's gnawing behaviors. Therefore, this paper predicts and analyzes children's gnawing behaviors based on machine learning [12]. The research content of this paper is divided into three parts: The first part is the relevant overview, including the significant difference analysis of mother's behavior response and the results measurement indicators; The second part is the prediction model performance and fitting analysis, which mainly includes the analysis of feature importance and prediction performance and the analysis of model fitting results; The third part is the optimization and application of the prediction model, which is divided into two parts: optimization results analysis and innovative design of gnawing toys.

2. Related Overview

2.1. Significant Differences in Maternal Behavioral Responses

In order to investigate whether there is a significant difference between the scores of different types of behavior responses of mothers to children's biting behavior, six types of behavior strategies are taken as an intra-subject factor, and one-way ANOVA is used to investigate. The results of one-way ANOVA of six types of behavior strategies of mothers to children's biting behavior are shown in Table 1:

Table 1. Single factor ANOVA of maternal behavior response

	Sum of squares	mean square	F	Significance
Family scene externalization	183.46	27.63	43.513	0.0008
School scene externalization	275.77	32.75	77.239	0.0007
Implicit family scenes	348.81	48.67	127.922	0.0005
Implicit school scene	318.39	45.28	117.485	0.0003

The results in Table 1 show that in the home scenario, children's F for episodic nibbling was

43.513, p=0.0008<0.001, and F for implicit nibbling equalled 127.922, p=0.0005<0.001; in the school scenario, F for episodic nibbling was 77.239, p=0.0007<0.001, and F for implicit nibbling equalled 117.485, p=0.0003<0.001. This suggests that there is indeed a significant behavioural strategy type effect on mothers' behavioural response scores, and that mothers' scores on different types of behavioural strategies are significantly different. To further identify mothers' main behavioural responses to their young children's external and implicit problem behaviours in home and school scenarios, two-by-two post hoc multiple comparisons were conducted on mothers' tendency to respond to the six behavioural responses based on the one-way ANOVA described above [13]. The results of the post hoc multiple comparisons showed that the most dominant behavioural responses of mothers to children's externally and implicitly problematic nibbling behaviour in different scenarios were reasoning and guidance and skill training, followed by reviewing themselves, then punishment and reprimand, and finally no action [14].

2.2. Outcome Measures

Recall rate is the number of correctly identified targets as a percentage of all targets in the test set, i.e. the percentage of cats correctly identified by the system as a percentage of the number of cats in the sample [15]. Accuracy is the percentage of correctly identified targets out of all targets identified, i.e. the percentage of all targets identified as cats by the system that are actually cats [16]. The recall is to assess whether the prediction is complete or incomplete, and the accuracy is to assess whether the prediction is accurate or not. The formulae for both metrics are shown below.

$$recall = \frac{CM}{CM + QB} \tag{1}$$

$$precision = \frac{CM}{CM + QT} \tag{2}$$

The recall rate expresses the proportion of real samples in all real samples, and the accuracy rate expresses the proportion of real samples in all positive samples. It can be inferred that the recall rate value can measure the integrity of the system's correct identification of objects, that is, the integrity of the tested target group's successful identification [17]. The accuracy rate value can measure the accuracy of the system in identifying objects, that is, the percentage of correct objects among the identified objects. It can be inferred from the above two formulas that there is an equilibrium relationship between the recall rate and the accuracy rate, and the trend of increase and decrease is opposite [18].

3. Prediction Model Performance and Fitting Analysis

3.1. Feature Importance and Prediction Performance

Firstly, the importance coefficient is used to analyze the influence factors of children's biting behavior. The importance of features in the random forest model and the AM is shown in Figure 1. Then 20 cross validation trainings were conducted on the importance of all factors, and the performance of the prediction model is shown in Table 2.

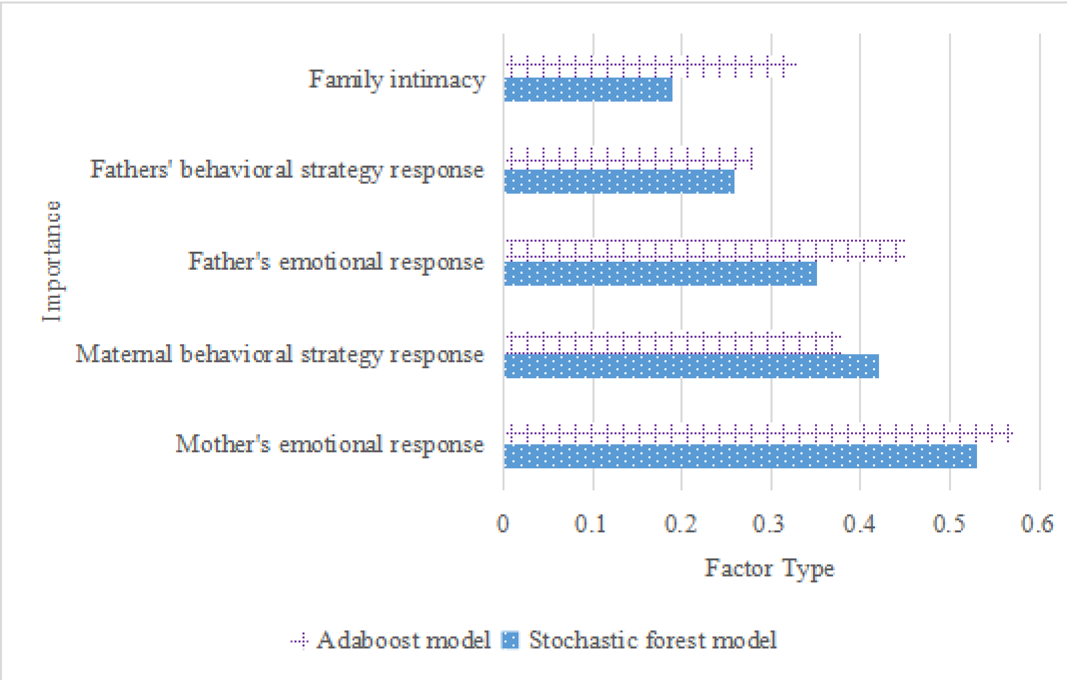

Figure 1. Importance scores of influencing factors

In the random forest model, mother's emotional response was the most important characteristic with a score of 0.53. The second most important characteristic was mother's behavioural strategy response with a score of 0.42. Father's emotional response, father's behavioural strategy response and family closeness were also important factors that could not be ignored. In the AM, again the mother's emotional response was the most important, with a score of 0.57; but the second most important feature was the father's emotional response; followed by the mother's behavioural strategy response, family closeness, and finally the father's behavioural strategy response.

Table 2. Model predictive performance

	Precision ratio(%)	Precision(%)	Recall(%)	F1(%)
Stochastic forest model	75.69	78.49	76.49	79.28
AM	77.57	81.27	79.55	82.44

When using the random forest model to predict children's chewing behaviour, it was able to achieve a detection rate of 75.69%, an accuracy rate of 78.49%, a recall rate of 76.49% and an F1 value of around 79.28%; in the AM, the detection rate, accuracy rate, recall rate and F1 value were 77.57%, 81.27%, 79.55% and 82.44% respectively. From the performance prediction results, it can be obtained that the prediction performance of the AM is better than the prediction performance of the random forest model. Therefore, in terms of prediction performance, the AM should be selected for predicting children's gnawing behaviour.

3.2. Analysis of Fitting Results

The 153 data were screened for correlation and 119 relevant data were selected as input feature values into the training data. The fitting results of the random forest model and the AM are shown in Table 3. The larger the ROC-AUC in the table, the better the fitting effect.

Table 3. Model fitting results

	Training ROC-AUC	Test ROC-AUC	New data ROC-AUC	Model fitting results
Stochastic forest model	0.9647	1	0.8828	General but possible over fitting
AM	1	0.9139	0.9566	Good but possibly over fitting

Analysis of the data in Table 2 shows that the AM has higher values for the training ROC-AUC and the new data ROC-AUC than the random forest model, and that the AM fits better than the random forest model. Both result scores in Table 2 have a value of 1 for the simulation result, indicating that both models are clearly over-fitted and that the dataset with a score of 1 is also over-learned by the trainer. The random forest model and the AM were better fitted than the AM, so the AM was chosen to predict children's chewing behaviour. However, the AM has the phenomenon of overfitting, so the model needs to be optimised.

4. Optimisation and Application of the Prediction Model

4.1. Analysis of Optimisation Results

The loss curves of the AM generated by the optimization training were compared with the loss curves before the optimization of the model, and the two curves were plotted under the same coordinate axis, as shown in Figure 2 below.

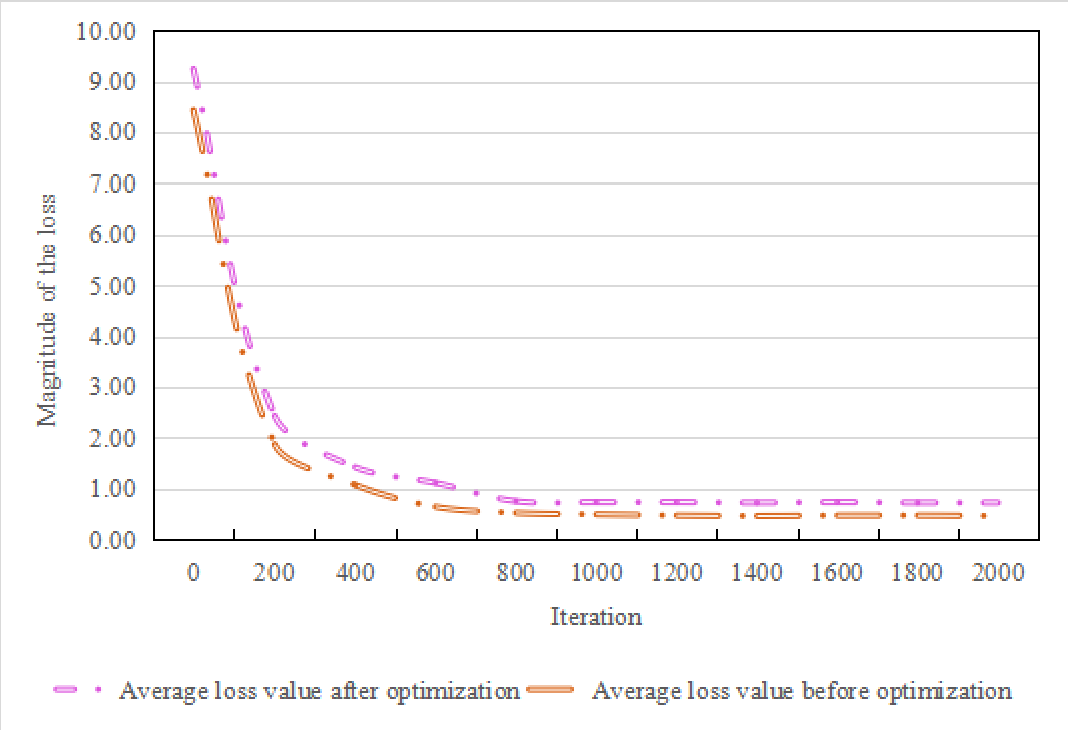

Figure 2. Average loss value comparison effect

From the analysis in Figure 2, it can be seen that the average loss value of the optimised model converges rapidly before 600 iterations of training, but the magnitude of convergence is not as large as that of the average loss value curve of the previous training, so we consider the convergence of the average loss value curve of the optimised model to be within the normal range, considering the overfitting phenomenon of the pre-optimised model. The average loss value curve of the optimised model is perturbed, but the magnitude of the perturbation is not large and is considered to be within the normal range. The average loss value of the optimised model gradually converges to a stable value of 0.72 between 800 and 2000 iterations, and the overall decreasing trend of the curve shows that the decreasing rate decreases with the increase of the number of iterations. 2.43 to 0.52. The optimized average accuracy curve did not show divergence and excessive fluctuations, and the stable value was within the normal range, so it was considered to be in line with the expected effect of children's gnawing behaviour prediction.

4.2. Innovative Design of Gnawing Toys

The prediction of children's gnawing behaviour was made through the optimised AM and the prediction results were used to design gnawing toys. Infants and toddlers perceive the world through the observation and touching of toy shapes and textures, and the gnawing stage of teething development is aided by the gnawing of toys. In the design and practice phase, the focus should be on increasing the orthodontic and cleaning functions of the gnawing toys, increasing the interactivity and fun of the products, and attracting infants and toddlers to use the gnawing products to improve their dental and oral health to varying degrees. The first stage of teething development is to improve the form of teething toys to relieve tooth soreness in the early stages of germination; the second stage of teething development is to add gnawing toys to assist in the correction of crooked teeth; the third stage of teething development is to add gnawing toys to assist in the cleaning function to develop good oral cleaning habits. The third stage of teething development is the addition of gnawing toys to assist with cleaning and good oral hygiene.

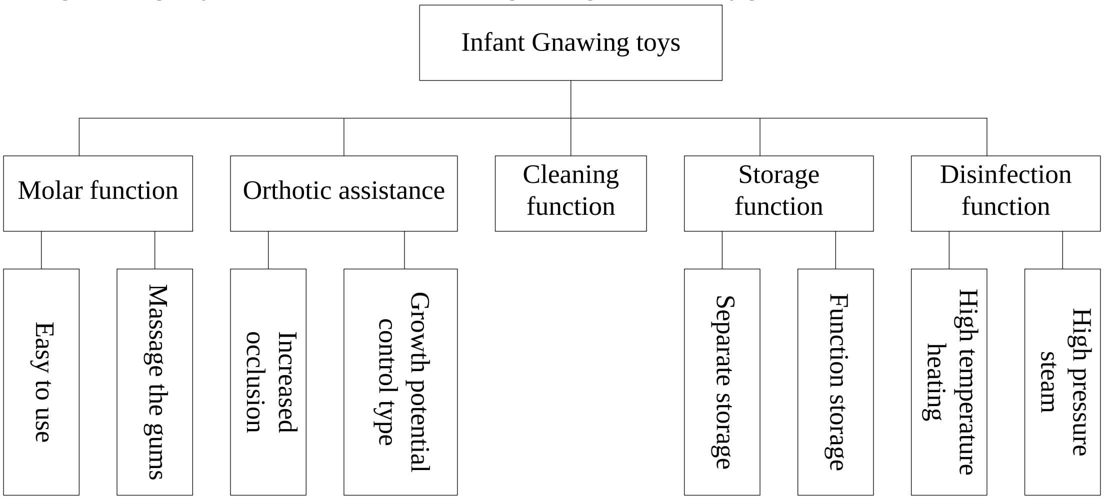

Figure 3. Toy design mind map

5. Conclusion

The generation of children's nibbling behaviour is closely related to parents, and machine learning can improve the accuracy of predicting children's nibbling behaviour, therefore, this paper predicts and studies children's nibbling behaviour based on machine learning algorithms. The following conclusions are drawn from this paper: through a comparative analysis of the random forest model and the AM, it is found that the prediction performance of the AM is better than that of the random forest model, and the fitting effect of the AM is also better, and the prediction effect of choosing the adaboost prediction model for predicting children's chewing behaviour is better, but The AM was over-fitted and needed to be optimised; a comparative analysis of the mean loss values before and after optimisation revealed that the stable value of the mean accuracy curve was within the normal range after optimisation, which was consistent with the prediction effect of children's chewing behaviour. Finally, the model was used to derive prediction results for the innovative design of gnawing toys. There are many areas for improvement in this paper.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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