INTELLIGENT DIET RECOMMENDATION POWERED BY BIG DATA AND DERIVATIVE DEEP LEARNING FOR CHILD NUTRITION

Mrs.P. Vanitha[1], Dr.P.Jayasree [2]

1 Ph.D Research Scholar, Department of Computer Science, Hindusthan College of Arts & Science, Coimbatore.
2 Dr.P.Jayasree, Professor, Department of Computer Applications, Hindusthan College of Arts &Science, Coimbatore.

Abstract

A novel Partial Effect Regression and Convergence-efficient Deep Belief Neural Network (PER-CDBNN) method is proposed based diet plan recommendation for big data analytics in child nutrition with several layers. In input layer, diet plan samples from corresponding big dataset are provided as input. Then, first hidden layer of deep belief neural network, Peirce's Criterion Probability-based pre-processing is applied to ensure robust cleaning and normality of big data. Next second hidden layer, a feature selection model called, Symbolic Regression and Partial Effect is applied by revealing inputs possessing most significant unique influence on outcome. Finally, to balance learning speed and prevent slow convergence, Convergence-efficient ReLU activation-based Classifier is employed to multiclass predictions for accurate diet plan recommendation. These uncovering constitute a paradigm shift toward proactive nutritional surveillance, enabling diet recommendation through Deep Belief Neural Network methods. Implementation of this could significantly boost early recommendation capabilities, clear way for timely nutritional interventions and contribute considerably to bringing about nutrition targets globally while reducing childhood mortality rates.

Keywords: Deep Learning, Peirce's Criterion Probability, Symbolic Regression, Partial Effect, Convergence-efficient ReLU

1. Introduction

Child health analytics on food habits necessitates keeping an eye on dietary patterns. Long Short Term Memory with Fully Connected neural network (LSTM-FC neural network) in [1] employing meticulous data preprocessing for handling missing values, normalization and balancing. A Multi-Head Attention (MHA) AI and (XAI) in [2] capturing complicated cross-feature dependencies. A gamification approach [3] provides digital application in AdobeXD. The cross-sectional study was carried out in [4] to compute association between dietary knowledge and overweight/obesity in children and adolescents. An adjusted logistic regression was carried out in [5]. A qualitative face-to-face inquiry was carried out in [6] with 15 mothers of school-aged children in South Australia. Dietary habits that were linked with the growth development of children aged less than 5years residing in rural Burkina Faso was presented in [7]. Symbolic regression method was proposed in [8] to train high-dimensional electronic health record (EHR) data accurately. An experimental study was conducted in [9] to analyze eating behavior of primary students. A comprehensive review exploring the role of parents and teacher along with environmental and socioeconomic aspects was investigated in [10]. Study was conducted in [11] to measure the ubiquity and ascertain the elements playing a part in this age group. A machine learning-based method for enhanced accuracy was presented in [12]. Yet another food

recommendation system employing artificial nutrition analysis was investigated in [13]. A data-driven study was conducted in [14] employing artificial intelligence (AI) and computer vision on children's health outcomes. A community-based nutrition mechanism was presented in [15]. A key objective is to visual insights into neural features impacting prediction. In order to achieve this, we perform a systematic analysis of PER-CDBNN for multiclass prediction. Peirce's Criterion Probability and Gaussian normal distribution method, Symbolic Regression and Partial Effect-based Feature and Convergence-efficient ReLU activation-based Classifier is developed in PER-CDBNN for improving overall prediction.

2. Related works

An eigen-based class activation method was proposed in [16] so as to impart users. Yet another method associating food habits with physical activity employing DL was presented in [17] to identify the correlation level. Various traditional food patterns and eating habits of school-aged children in South Australia were explored in [18]. In [19], an AI-based nutrition recommendation method generating balanced and customized weekly meal plans tailored to nutritional requirements and inclinations of healthy adults was investigated to address modern dietary challenges. A hybrid diet recommendation mechanism combining ML and big data was investigated in [20] to provide healthy dietary recommendations. Yet another comprehensive analysis was conducted in [21] using ML therefore contributing to obesity risk diagnosis. An ensemble of DL and ML techniques were applied in [22] for early detection while lesser childhood mortality rates. A modified activation function was employed in [23] that by using hyper parameter fine tuning reduced error. A gamification approach was conducted in [24] to identify influence of digital game in analyzing nutritional benefits with improved accuracy. Yet another cross sectional study was conducted in [25] to analyze obesity in children age between 8 and 18 years with higher precision. A cross sectional survey was conducted in [26] among low income families with young children related to food security. Naïve bayes ML technique was applied in [27] to provide diet suggestion for not only predicting the disease but also predict disease based on the symptoms. Yet another DL based technique to recommend best prospective diet chart was designed in [28] accurately. An AI based web application was designed in [29] for not only providing diet planning but also providing recommended exercise precisely. Focusing on precision or accuracy along, a deep belief neural network method with improved accuracy and minimal root mean square is designed using PER-CDBNN.

3. Materials and methodology

The diet-plan-recommendation dataset includes data obtained from two different sources and taken from https://www.kaggle.com/code/kishoreharshankumar/diet-plan-recommendation/input. It predicts diet plan based on calories to maintain weight. The Data Plan Recommendation csv file includes 11 features and 10726 samples.

Table 1 Details of diet-plan-recommendation dataset

S. No	Features	S. No	Features
1	ID	7	BMR
2	Age	8	Activity level
3	Weight	9	Calories to maintain weight
4	Height	10	BMI tags
5	Gender	11	Label
6	BMI		

3.1 Partial Effect Regression and Convergence-efficient Deep Belief Neural Network

Proposed PER-CDBNN method is with intent of improving precision and accuracy for diet recommendation in child nutrition comprising big data.
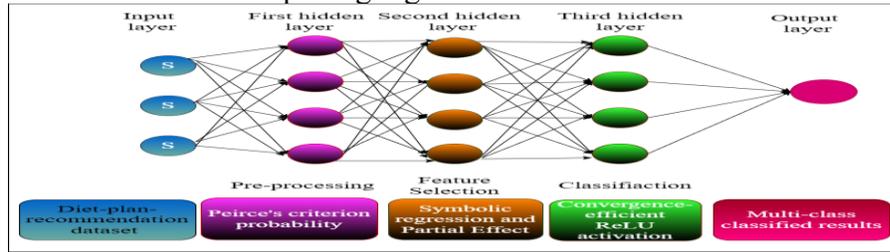

Figure 1 Architecture of PER-CDBNN method

As shown in the above figure 1, proposed architecture of deep learning method comprises. The elaborate description of proposed method is provided in following sub-sections.

3.2 Input layer

The raw big data input obtained from diet-plan-recommendation dataset provided as input to input layer. The big data input vector is formulated as given below.

$$IV = \begin{bmatrix} S_1F_1 & S_1F_2 & ... & S_1F_N \\ S_2F_1 & S_2F_2 & ... & S_2F_N \\ ... & ... & ... & ... \\ S_MF_1 & S_MF_2 & ... & S_MF_N \end{bmatrix}, M = 10725, N = 11 \tag{1}$$

From the above mathematical formulate (1) the big data input vector 'IV' is provided as input layer with 'M' samples 'S_M' and 'N' features 'F_N' respectively. The raw big data obtained from input vector are provided as input to first hidden layer where pre-processing is performed.

3.3 Peirce's Criterion Probability-based pre-processing model

Peirce's Criterion Probability-based pre-processing is applied for outlier detection. By using Peirce's Criterion Probability-based pre-processing to BMI, BMR and calories_to_maintain_weight can be transformed to approximate a normal distribution. It helps to frequently observed skewed and not said to be normal. The distribution should be more symmetric and hence data transformations have to be applied to ensure normality. Also, calorie data can also be highly variable and susceptible to extreme values. Peirce's Criterion Probability to this calorie data helps in robust big data cleaning. Figure 2 illustrates structure of Peirce's Criterion Probability-based pre-processing model.
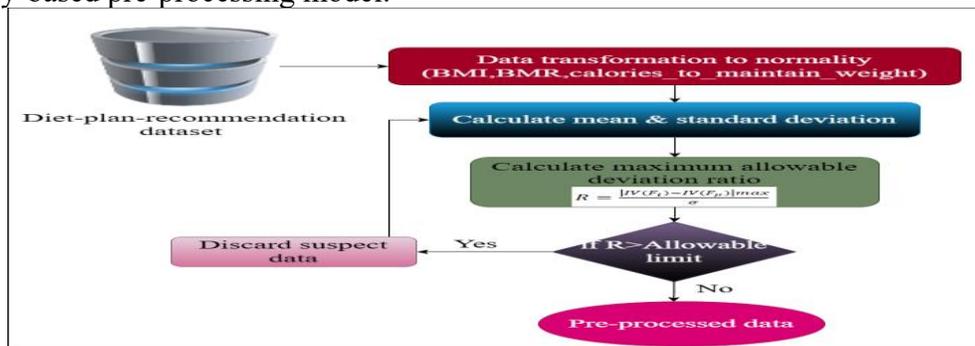

Figure 2 Structure of Peirce's Criterion Probability-based pre-processing model

As shown in above figure, with raw big data obtained from diet-plan-recommendation dataset. Initially, ratio of maximum allowable deviation of a measured value from data mean to standard deviation results for BMI and Calorie data is obtained. The suspicious measurement is discarded. The process gets repeated sequentially until no more data measurements for BMI, BMR and calories_to_maintain_weight data need to be discarded. The three features BMI, BMR and calories_to_maintain_weight are subjected to process of transformation to normality during data

cleaning phase. Then, the ratio of maximum allowable deviation of a suspect data point from data mean to standard deviation is mathematically formulated as given below.

$$R = \frac{|IV(F_i) - IV(F_\mu)|max}{\sigma}$$ (2)

From equation (2) ratio 'R' is measured based on measured big data value of two features 'F_i', mean value of two features 'F_μ' and sample deviation 'σ' of two features. This in turn identifies and eliminates erroneous values ensuring robust and reliable per-processed samples. The pre-processed samples are fed to second hidden layer to perform relevant feature selection.

3.4 Symbolic Regression and Partial Effect-based Feature Selection

Symbolic Regression and Partial Effect-based Feature Selection is used to not only enhance the accuracy of result expressions by confronting the issue of over fitting but also reduce root mean square error by revealing inputs that have most significant unique impact on outcome.
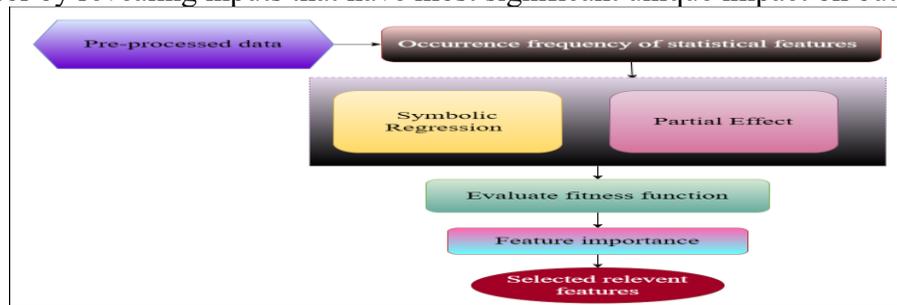

Figure 3 Structure of Feature Selection model

In figure3, feature selection results are obtained. The Partial Effect revealing feature importance is also considered as a criterion in feature selection. By using Partial Effect as fitness function with transformation function, complexity and errors in expressions is minimized. The Transformation-Interactional-Rational-Representation (TIRR) constrains search space in simple mathematical expressions, circumventing complex expressions generation, emphasizing solutions in affine combinations form applied to polynomials (interactions). Let us consider the 'N' features '$F_1, F_2, \ldots, F_N$'. Then, TIRR function is defined as given below.

$$IT(F) = \prod_{i=1}^{N} F_i^{k_i}$$ (3)

From equation (3) interaction term 'IT' for each feature 'F' is defined based on vector with feature significance. Let '$TF: \mathbb{R} \to \mathbb{R}$' denote transformation function, then '$IT(F)$' is tuple '(TF, k)' formulated as given below.

$$TF(F) = \sin(TF.IT)(F)$$ (4)

From equation (4) strength vector 'k' is used interaction. Then, affine combination results are generated as given below.

$$f'(F) = \sum_{j=1}^{m} w_j.IT_j(F)$$ (5)

By using (5),'w_j' denotes coefficient of '$j - th$' interaction term 'IT'. As a result, expressions non-linearity is encapsulated via interaction function strengths and transformation function. Thus, essential features are selected for diet plan recommendation for child nutrition.

Let '$FS = f(F, \beta)$' be model to be interpreted, where 'F' denotes features and 'β' denotes the learned vector or its corresponding values. The Partial Effect for a variable 'j' is arrived at by obtaining partial derivative of 'f'' with respect to 'F_j' and is as given below.

$$PE_j = \frac{\partial f'}{\partial F_j}(F, \beta)$$ (6)

The symbolic regression returns a mathematical expression that best fits data 'f'', purpose of employing a known representation is that procedure of automatized. Then derivative of 'TF' expression with respect to any given feature 'F_j' is obtained as given below.

$$\frac{\partial f'}{\partial F_j} = w_1 TF_1'(F) + w_2 TF_2'(F) + \cdots + w_m TF_m'(F) \tag{7}$$

$$TF_i'(F) = TF_i'\big(IT(F)\big).IT'(F) \tag{8}$$

$$IT'(F) = k_j \frac{IT(F)}{F_j} \tag{9}$$

From equations (7), (8) and (9) features with frequently high absolute partial effect values are selected as salient or relevant, on other hand for contrast with near-zero (PE) are irrelevant, simplifying model. The relevant features selected via second hidden layer are then provided as input to third hidden layer for analyzing big health data towards diet plan recommendation.

3.5 Convergence-efficient ReLU activation-based Classifier

Convergence-efficient ReLU activation-based Classifier controlling the step size for updating model weights by introducing higher non-linearity and facilitate smooth transition from positive to small negative values during training to balance learning speed and preventing slow convergence. The mathematical formula for ReLU activation function is given as below.

$$f(p) = \begin{cases} 0, for\ p < 0 \\ p, for\ p \geq 0 \end{cases}, where\ p \in PS[FE] \tag{10}$$

From equation (10), 'p' and '$f(p)$' denotes the input and output of ReLU on each channel. If ReLU input is greater than '0', then output is activated and said to be equal to input, on contrary, if ReLU input is smaller than '0', output is not activated and said to be no equal to zero. Hence, a functionality restoring the original derivative function that allow absolute values of small negative gradient introducing higher nonlinearity in output to enable straightforward transformation from positive to small negative values.

$$f'(p) = \begin{cases} 1 - e^{\alpha p}, for\ p < 0 \\ p, for\ p \geq 0 \end{cases}, where\ p \in PS[FE] \tag{11}$$

From the above equation (11) 'p' denote the input for non-linear activation function 'f'' with 'α' representing a coefficient factor lying between 0.01 and 0.05. By introducing coefficient factor aids in controlling negative values from each layer. To be more specific if 'α=0' then activation function turns out to be as given below.

$$f''(p) = \max\big(0, f(p)\big) = \max(0, p) \tag{12}$$

Finally based on above Convergence-efficient ReLU activation-based Classifier results (12) 'f'''', the proposed method use cross-entropy loss function for multi-class classification. By optimizing cross entropy loss, classifier model aims to improve its performance for prediction of diet plan based on calories to maintain weight. The mathematical equation for cross-entropy loss function is represented as given below.

$$CL(q, q') = -(q\log\ (Pred) + (1 - q)\log(1 - p)) \tag{13}$$

$$CL(q, q') = -\sum\big(q\log\ (q')\big) \tag{14}$$

From the above equations (13) and (14), 'q' denotes true label vector and 'q'' denotes the predicted probability distribution between classes with '$Pred$' denoting the predicted probability observation of class respectively. The pseudo code representation of PER-CDBNN with big data input for child nutrition is given below.

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, …, S_M\}$', Features '$F = \{F_1, F_2, …, F_N\}$'
Output: robust and intelligent diet plan predictor
Step 1: **Initialize** '$M = 10725$', '$N = 11$', '$0.00001 \leq \alpha \leq 0.05$'
Step 2: **Begin**
//Input layer
Step 3: **For** each Dataset 'DS' with Samples 'S' and Features 'F'
Step 4: Formulate input vector according to (1)
Step 5: **End for**
//**First hidden layer [pre-processing]**
Step 6: **For** each Dataset 'DS' with Samples 'S' and Features 'F'
Step 7: Generate the ratio according to (2)
Step 8: **If** '$\|IV(F_i) - IV(F_\mu)\| > \|IV(F_i) - IV(F_\mu)\|max$'
Step 9: **Then** eliminate that outlier
Step 10: **Else** retain original number of measurements
Step 11: **End if**
Step 12: **Return** pre-processed samples 'PS'
Step 13: **End for**
//**Second hidden layer [feature selection]**
Step 14: **For** each Dataset 'DS' with pre-processed samples 'PS' and Features 'F'
Step 15: Generate Interaction Term results according to (3)
Step 16: Formulate Transformation Function results according to (4)
Step 17: Generate affine combination results according to (5)
Step 18: Generate partial derivative of 'f'' with respect to 'F_j' according to (6)
Step 19: Generate partial effect values according to (7), (8) and (9)
Step 20: **If** '$PE_j \geq 0.5$'
Step 21: **Then** features are significant and selected
Step 22: **Return** features selected 'FS'
Step 23: **End if**
Step 24: **If** '$PE_j < 0.5$'
Step 25: **Then** features are not significant and not selected
Step 26: **Go to** step 15
Step 27: **End if**
Step 28: **End for**
//**Third hidden layer [classification]**
Step 29: **For** each Dataset 'DS' with pre-processed samples 'PS' and features selected 'FS'
Step 30: Formulate ReLU activation function according to (10)
Step 31: Generate non-linear activation function according to (11)
Step 32: Generate Convergence-efficient ReLU activation-based Classifier according to (12)
Step 33: Generate cross-entropy loss function results according to (13) and (14)
Step 34: **Return** multi-class classified results
Step 35: **End for**
Step 36: **End**

Algorithm Partial Effect Regression and Convergence-efficient Deep Belief Neural Network for child nutrition

4. Experimental setup and discussion

Proposed PER-CDBNN method and existing Long Short-Term Memory-Fully Connected Neural Networks (LSTM-FN neural networks) [1] and Multi-Head Attention (MHA) and Explainable Artificial Intelligence (MHA and XAI) [2] are implemented in Python.

4.1 Performance analysis of root mean square error

The root mean square error '$RMSE$' is one of commonly employed measures of divergences between true 'Act'or 'Pre'predicted values. The RMSE is represented as given below.

$$RMSE = \sqrt{\frac{(Act-Pre)^2}{M}} \tag{15}$$

From equation (15) '$RMSE$' is estimated with respect to 'M' number of samples.
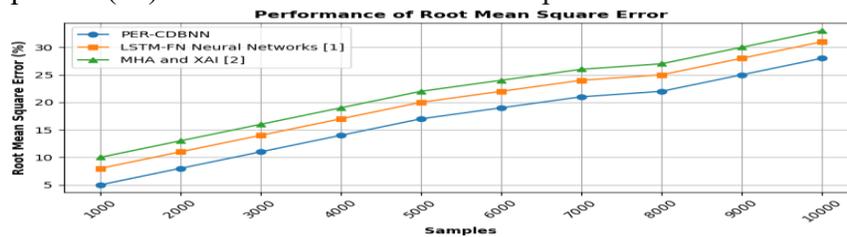

Figure 9 Root mean square errors versus samples

Figure 9 Represent RMSE using PER-CDBNN reduces by 23% and 38% over [1], [2].

4.2 Performance analysis of precision, recall and accuracy

Precision performance metric concentrates on the quality of recommendations that were actually provided. Precision is mathematically defined as given below.

$$Pre = \frac{TP}{TP+FP} \tag{16}$$

The recall performance metric evaluates the method's ability to identify all the items that are relevant to the children's needs from the entire dataset. Recall and accuracy is mathematically defined as given below.

$$Rec = \frac{TP}{TP+FN} \tag{17}$$

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \tag{18}$$

From the above equations (16), (17) and (18) precision 'Pre', recall 'Rec' and accuracy 'Acc' is measured based on the true positive value 'TP', false positive value 'FP', true negative value 'TN' and false negative value 'FN' respectively.
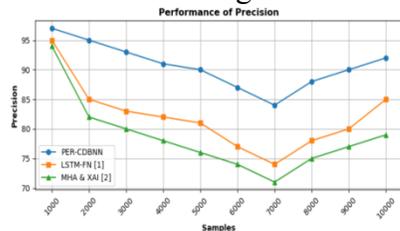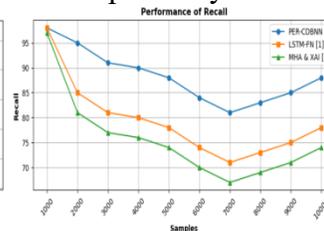

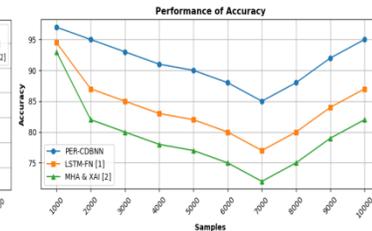| Figure 10 Precision | Figure 11 Recall | Figure 12 Accuracy |

The figure 10, 11, 12, shows better PER-CDBNN technique result with improved Precision, recall and accuracy by 10% and 13%, Recall by 10% and 15% accuracy 8% and 13% over [1], [2]

5. Conclusion

The proposed PER-CDBNN method for predicting diet plan based on calories is done via deep learning technique by performing the tasks of pre-processing, feature selection and classification. Experimental results prove that PER-CDBNN method efficiently differentiates between different classes by bridging trust gap and enable pediatrics in making make accurate assessments with minimal error.

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