Children Food Intake Level Based on Deep Learning Using Variational Autoencoder-Gated Recurrent Neural Network (Vae-Grn2)

P. Jeyanthi(✉) and R. Durga

Department of Computer Science, Vels Institute of Science, Technology and Advanced Studies, Chennai, India
jeyanthirajaprabakaran@gmail.com, durga.scs@vistas.ac.in

Abstract. Malnutrition in children has been studied in recent years as the insufficiency to consume essential nutrients, resulting in stunted growth, lower immunity, and impaired development. Additionally, according to World Health Organization (WHO) standards, malnutrition is categorized into three major groups: underweight, stunted growth, and wasting. However, training diet controls the accuracy and memory, which is limited by the volume and bias of databases in typical nutritional advice systems. To address this issue, we proposed a Variational Autoencoder-Gated Recurrent Neural Network (VAE-GRN2) framework to predict caloric and nutrient levels in children. Furthermore, the pre-processing of the data obtained from the dataset can be conducted with the help of the C-Score Normalization (CSN) algorithm, which defines errors, duplicates, and missing data. Then, the impact ratios of the various levels of food intake, based on their nutrient profiles, are calculated using the Contrastive Nutrient Impact network (CNIN) model. Additionally, optimal features can be selected using the Deep Variance Sequence Generating Feature Selection (DVSGFS) technique to identify informative nutrients in temporal dependencies and predictive performance. Finally, we proposed a VAE-GRN2 model based on a deep learning (DL) algorithm to improve the accuracy of detecting children's dietary status by generating feature vectors. Furthermore, the presented methods can detect food intake levels with a high 97% accuracy rate in performance metrics such as precision, recall, F1-score, accuracy, and time complexity.

Keywords: Children nutrients · food intake level · deep learning · DVSGFS · feature selection · impact rate · and VAE-GRN2

1 Introduction

Due to restricted food production, meeting everyone's requirement for food items (e.g., vegetables, fruits, milk, wheat, etc.) has become a big difficulty. Food availability referred to food supply both nationally and domestically. Individuals and households have access to food under the entitlement system, even if they do not have enough money to purchase nutritious food. There are several author-defined meanings of food security that all convey the same concept. Food security refers to the situation in which everyone has enough nutritious food to live a healthy and active life [1].

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Children are targeted and made vulnerable by food marketing. One of the top global priorities for lowering obesity, dietary risks, and the prevalence of communicable diseases is shielding kids from deceptive food marketing. Children's perceptions of food and food brands, as well as their consumption, weight, and purchase behavior, are all influenced by their exposure to food marketing [2]. The reach, frequency, and persuasive power of marketing which include both design and content determine its influence. Additionally, the majority of developed nations are capitalist democracies where corporate profits and freedom of speech frequently trump the health of children [3]. However, many nations have enacted strict rules over the past few years that restrict certain aspects of food marketing to children.

However, obstacles remain when developing preventative strategies or treatments for a specific location. For instance, parental feeding habits significantly influence childhood obesity. Therefore, if a community aims to establish a tailored policy or intervention that best fits the local context, determining which indicator best represents a general element is challenging [4].

The immune systems of children are more susceptible to illnesses than those of adults. Because malnourished children's immune systems are compromised, they are more likely to die. On the other hand, little is known about the underlying reasons of immune function impairment and how hunger is related to it. Nutritional therapies are thought to be economical methods of treating or avoiding malnutrition [5]. This is especially crucial for youngsters at risk of problems linked to their dietary habits. Health, besides childhood health, has a significant impact on their physiological development.

1.1 Contribution of Work

- The main contribution of this section is the proposed VAE-GRN2 model for predicting children's calorie and nutrient intakes in temporal dietary patterns.
- The CSN algorithm is used to effectively handle errors, duplicates, and missing data in the dietary datasets.
- The CNIN model was developed to calculate the impact ratios of different dietary intakes of specific nutrients.
- The DVSGFS technique is proposed to select optimal and informative features to capture temporal biases and improve prediction accuracy.
- The proposed technique contributes to better health monitoring and nutrition planning by demonstrating improved performance in improved dietary status prediction in children.

1.2 Objective of the Work

By integrating advanced data pre-processing, feature selection, and nutrient impact modeling techniques, VAE-GRN2 develops a deep learning framework to predict children's caloric and nutrient intake accurately.

1.3 Motivation of the Work

- The CSN algorithm was provided to analyze incomplete, duplicate, and incorrect dietary data.

- Enhance the understanding of how various nutrient intakes affect children by modeling the ratios of nutrient impacts using the CNIN.
- Enhance feature selection to facilitate time analysis using the DVSGFS technique.
- Finally, enhance predictive power with the VAE-GRN2 model in measuring the dietary condition of children.

2 Literature Survey

Two individual and household-based categorization systems were applied in this work to determine the performance of four Machine-Learning (ML) algorithms in predicting undernutrition [6]. The analysis process involves ANN and K-Means clustering types of ML analysis [7]. The present data set of this study was based on provincial general hospital (RSUP) statistics of cases of child nutrition in the previous year.

The Decision Tree (DT) algorithm and the K-means clustering analysis tool were employed by the study [8] to investigate the relationship between vitamin and mineral consumption and anaemia. In determining the correctness of the ML model, the data was balanced and regularized using an ensemble-weighted clustering approach. Linear regression was used to perform a correlation analysis between Body Mass Index (BMI) and ingestion of live microbes. The Logistic Regression (LR) was used to analyses the relationship between the existence of abdominal obesity and consumption of live microbes [9].

A sample of 2013 children was selected, and information about all the mentioned characteristics was provided [10]. To predict the state of childhood anemia, we applied multiple machines learning methods, including the support vector machines (SVM) approach. The Random Forest (RF) model outperformed all other machine learning models in detecting child nutritional deficiencies. However, these studies, which commonly employ logistic and multilevel models, were unable to identify the most significant predictors [11].

The study process comprises analyzing the system and designing machine learning applications utilizing the Multiple Linear Regression technique. The developed approach may then be used to forecast the nutritional status of children in Aceh in a timely, precise, and accurate manner. Furthermore, among the five machine learning methods, the xgbTree approach outperforms the generalized linear mixed model [12].

The machine learning algorithms range from basic ones, e.g., Logistic Regression and K-Nearest Neighbor, to more contemporary ML models [13]. For the most part, accuracy scores range significantly higher or lower than the 75% baseline accuracy, where the best LSTM-FC models achieved 91%. This validates the use of LSTMs for modelling time-series data. Most studies suffered from the limitation of self-reported or cross-sectional data, limiting the ability to make causal inference and reducing the validity.

The paper [14] introduces a novel probabilistic forecasting technology, GRU, to foresee the deformation of landslides on a formative basis. The novel [15] aimed to minimize the effect of race on models derived from data using Adversarial Variational Autoencoders (AVAEs). However, race is often excluded as an input variable because it is highly correlated with many other variables. Introduces [16] a conditional GAN that produces realistic, shape-constrained food images with known shapes/containers, which has direct applications in augmenting food-image datasets used to predict portion size and thus intake. Empirically compare GAN methods with other methods on structured clinical data [17]. The model is useful when selecting GAN variables for intake levels (continuous nutrients, counts, and categorical food types).

3 Proposed Methodology

The proposed methodology starts with collecting children's nutritional intake information, which can include questionable, incomplete, and inconsistent records. To mitigate this issue, the first part of the methodology is to implement a CSN algorithm as a preprocessing action to identify and clean the questionable records, tackle missing information, and eliminate duplicates. The selection of the proposed generative method was based on its ability to adequately model the high-dimensional, complex, and often missing food intake data found in children. Traditional statistical tools have weaknesses in their ability to reflect nonlinear relationships among different food types, portion sizes, and demographic or behavioral variables. In contrast, generative models such as VAEs and GANs can capture the hidden structure of food data and learn latent representations that generate realistic synthetic models. This can be advantageous when the datasets used in dietary intake studies are small, biased, or limited by privacy considerations (especially in the case of studies of children). Reducing biases across population groups allows for extrapolation of small child nutrition datasets. It provides a proper scaling solution to simulate realistic intakes across a range of health conditions and environmental settings.

As shown in Fig. 1 the data to ensure the model receives the best/cleanest input data. Next, the CNIN will determine nutrient impact ratios to quantify the nutrient make-up of food items and eating patterns over the food record period. The DVSGFS method will be used to select the most relevant and informative time-related features from the dataset to increase prediction performance and lower model complexity. The selected features will be fed into the "core" predictive model, the VAE-GRN2. This hybrid model will use the generative properties of the VAE to generate latent dietary patterns from the data. At the same time, the GRN2 captures the sequential learning associated with incorporating time while modeling the nutritional intake data.

3.1 Dataset Description

The nutrition data set is a finished statistical summary of information regarding the nutritional content of different food materials. It contains numerous types of information, including amounts of macro- and micronutrients, calories, vitamins, minerals, and other relevant nutritional properties. All the food products enable researchers, nutritionists, and health enthusiasts to study them, decode their nutritional value, categorize eating-style habits, develop personalized diets, and investigate the dietary effects on overall well-being and health. It is a remarkable source for rigorous research, imagining new nutritional approaches using tools, and making rational decisions in nutrition and dietetics, as the database is both gigantic and accurate. This dataset contains 8788 observations and 76 features.

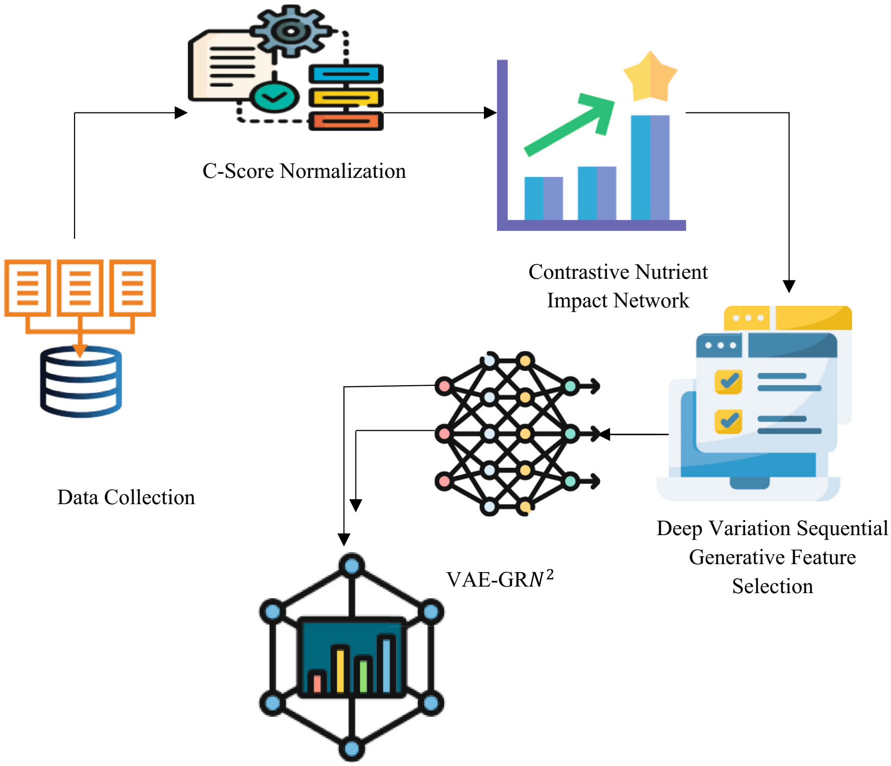

Fig. 1. Architecture Diagram of the Proposed Method

1		name	serving_size	calories	total_fat	saturated_fat	cholesterol	sodium	choline	folate	folic_acid
2	0	Cornstarch	100 g	381	0.1g		0	9.00 mg	0.4 mg	0.00 mcg	0.00 mcg
3	1	Nuts, pecans	100 g	691	72g	6.2g	0	0.00 mg	40.5 mg	22.00 mcg	0.00 mcg
4	2	Eggplant, raw	100 g	25	0.2g		0	2.00 mg	6.9 mg	22.00 mcg	0.00 mcg
5	3	Teff, uncooked	100 g	367	2.4g	0.4g	0	12.00 mg	13.1 mg	0	0
6	4	Sherbet, orange	100 g	144	2g	1.2g	1mg	46.00 mg	7.7 mg	4.00 mcg	0.00 mcg
7	5	Cauliflower, raw	100 g	25	0.3g	0.1g	0	30.00 mg	44.3 mg	57.00 mcg	0.00 mcg
8	6	Taro leaves, raw	100 g	42	0.7g	0.2g	0	3.00 mg	12.8 mg	126.00 mcg	0.00 mcg
9	7	Lamb, raw, grounc	100 g	282	23g	10g	73mg	59.00 mg	69.3 mg	18.00 mcg	0.00 mcg
10	8	Cheese, camembe	100 g	300	24g	15g	72mg	842.00 mg	15.4 mg	62.00 mcg	0.00 mcg
11	9	Vegetarian fillets	100 g	290	18g	2.8g	0	490.00 mg	82.0 mg	102.00 mcg	0.00 mcg

Fig. 2. Nutrition Dataset

The Nutrition Dataset (Fig. 2) provides a clear representation of the nutritional parameters analyzed. These dietary components may include various macronutrients (e.g., carbohydrates, proteins, and fat), micronutrients (e.g., vitamins and minerals), calories, as well as any other nutrition variables that may be handy in the provision of the meaning of what has been taken and the nutritional condition.

3.2 Pre-processing C-Score Normalization

To accurately estimate the level of nutrient intake in children, it is necessary to process the raw dietary data as strictly as possible, minimizing discrepancies, unavailable data, and data scaling errors. A typical approach to normalizing raw nutrient intake is to convert it to a C-score that can be compared with a person's intake and a specific dimension. Observed nutrient intake is compared to amounts of RDI, and then individual variability is corrected using the C-score normalization method. In the following section, representative equations are provided to clarify the normalization process:

$$Z_i = \frac{X_i - \mu}{\sigma} \tag{1}$$

where X_i the observed intake of nutrient is μ is the mean intake across the dataset, and σ is the standard deviation, such that the data can now be uniformly scaled. The RDI ratio is then calculated as:

$$R_i = \frac{X_i}{RDI_i} \tag{2}$$

With RDI representing the Recommended Dietary Intake for nutrient based on age, gender and physical activity. To evaluate how much a person's intake exceeds, not only the recommended amount, but the absolute difference is calculated:

$$D_i = |X_i - RDI_i| \tag{3}$$

This assists in detecting under- or over-consumption. The crux of the normalization is the C-score itself, defined as:

$$C_i = \frac{X_i - RDI_i}{\sigma} \tag{4}$$

In Eq. (4) X_i is the true observed intake of nutrient by the child, RDI is the Recommended Dietary Intake for nutrient I that is based on the child's age, gender and activity level, and σ is the standard deviation in that nutrient's intake among the population. This formula portrays how many standard deviations a child's intake is above or below the recommended level to objectively identify under- or over-nutrition.

$$C_{total} = \frac{1}{n}\sum\nolimits_{i=1}^{n} C_i \tag{5}$$

Computes the composite C-score that is achieved by averaging all the individual nutrient C-scores. C_{total} is the overall dietary balance value of the child, C_i is the normalized value of the C-score of individual nutrients i, and n is the number of nutrients. This cumulative score takes a complete perspective of the child's nutritional intake relative to the dietary recommendations that may be utilized as an input to health prediction models by the use of ML.

3.3 Contrastive Nutrient Impact Network (CNIN)

The CNIN is a new DL model that leverages contrastive representation learning to assess the impact rates of food products on a nutritional profile. In the case of a deployed nutrition dataset containing 77 nutritional attributes, CNIN aims to learn the nutritional embedding by distinguishing between the rates of nutritional health impacts caused by food items rated as close and those rated as dissimilar. First, foods are encoded as high-dimensional embeddings by sharing the same encoder network.

$$S_{i,j=}C_{total}\begin{cases} 1, \ if\, |y_i - y_j| < \epsilon \\ 0, \ otherwise \end{cases} \tag{6}$$

where y_i and y_j are the true impact rates for items i and j, and ϵ is a small threshold that determines the degree of similarity. The cosine similarity between two latent embedding's z_i and z_j is calculated as follows:

$$sim\left(z_i, z_j\right) = \frac{z_i \cdot z_j}{||z_i||.||z_{j||}} \tag{7}$$

The similarity score is then used in the NT-Xent contrastive loss which promotes similar pairs to be near each other in embedding space and dissimilar pairs to be farther apart. Once embeddings are learned, a regression head g $(\cdot)$ maps the latent embedding to an estimated impact rate:

$$y_i = g(z_i) \tag{8}$$

The difference between the predicted impact y_i and true value is minimized using the mean squared error loss.

$$\mathcal{L}_{regression} = \frac{1}{N}\sum\nolimits_{i=1}^{N}(y_i - y_i)^2 \tag{9}$$

The regression loss function in the equation represents an average of all measured squared differences between the actual rate and the impact y_i the predicted value, it is essential to note that N is the total number of samples, and each pair of values.

3.4 Deep Variation Sequential Generative Feature Selection (DVSGFS)

In predicting nutrient intake levels, the Deep Variation Sequential Generative Feature Selection (DVSGFS) technique identifies and selects the most informative nutrients by modelling their temporal dependencies and contributions to predictive performance. DVSGFS leverages a variation Autoencoders framework with a sequential generative model to capture the complex patterns in children's dietary intake over time.

$$\mathcal{L}_{ELBO} = E_{q\varnothing}(z|x)\left[log_{p\theta}(x|z)\right] - KL(q_{\varnothing}(z|x)||p(z)) \tag{10}$$

where x Dietary features sequence input (e.g., vector of daily nutrient intake for child), z: Latent variable that captures compressed, useful features $log_{p\theta}(x|z)$ Decoder (generative) model that decodes and reconstructs nutrient intake from latent space $q_{\varnothing}(z|x)$ Encoder (inference) model that estimates latent variable distribution KL: Kullback-Leibler divergence regularizes the latent space.

$$\mathcal{L}_{seq} = \sum\nolimits_{t=1}^{T} [E_{q\varnothing}(z_t|x \leq t)\left[logp(xt|zt)\right] - KL(q(zt|x \leq t)||p(z_t))] \tag{11}$$

where xt Nutrient intake at time step $x \leq t$ Nutrient intake history up to time, z_t Latent feature representation at time, captures temporal dependencies in nutrient intake and dynamically selects features across the sequence.

$$\mathcal{L}_{sparsity} = \lambda \sum\nolimits_{i=1}^{d} \pi_i \tag{12}$$

where d is the total number of nutrients, π_i is the selection probability for nutrient i, and λ is the hyper parameter that controls the level of sparsity, Encourages the model to choose fewer but more informative nutrients, discouraging over fitting.

3.5 Variational Autoencoder-Gated Recurrent Neural Network (VAE-GRN2)

In this section, the proposed VAE-GRN2 model is used to predict children's caloric and nutrient intake. Furthermore, users can get customized nutrient intake based on data collected from the dataset through the VAE-GRN2 model. A differential autoencoder network processes and analyzes input information such as weight, height, and age, and then estimates the user's dietary requirements and informational features in latent space to optimize the input information into a generated feature representation. The VAE-GRN2 is a model that can forecast intake and generate a sequence of children's food, as well as their nutrient intake levels. The created nutrient intake plan can be modified according to the nutrient sizes and characteristics obtained from the database, which is classified by nutrient intake, energy, nutrition, and the user's specific needs.

As indicated in Eq. 13, a recurrent neural network generates a set of nutrients, and the hidden vectors are used as input to calculate the daily nutrient plan, which effectively predicts the nutrients level. Let's assume $h(t)-$ hidden state at time, $(t)-$ time, $GRN2-$ gate recurrent neural network, $Z-$ latent vector.

$$h(t) = \mathcal{L}_{sparsity} \begin{cases} GRN2(Z) & for\, t = 1 \\ GRN2(h(t-1)) & for\, t > 1 \end{cases} \tag{13}$$

Calculate the estimated nutrient intake class for the previous latent state GRN2according to Eq. 14 and 15. Let's assume f_m- fully connected layer, $O(t)-$ output class of nutrient time, $\hat{y}_t-$ predicted nutrient classes,

$$O(t) = Soft_{Mas}(f_m(h(t))), t = [1,6] \tag{14}$$

$$\hat{y}_t = \underset{c}{argmax}(O(t)), t = [1,6] \tag{15}$$

The most suitable class for a food product is identified by manipulating the class probability as shown in Eq. 16 and 17. It uses a fully connected layer to calculate and predict the nutrient level, total energy, and nutritional value. Let's assume $\hat{n}-$ nutrient values $\widehat{E}_I-$ predict the total energy, $f_{EI}-$ energy fully connected layer

$$\widehat{E}_I = \sum_{t=1}^{T} f_{EI}(h(t)) \tag{16}$$

$$\hat{n} = \sum_{t=1}^{T} f_{nutr}(h(t)) \tag{17}$$

Calculate the deviation between the predicted caloric intake of the nutrient plan and the mean square error, as shown in Eq. 18. Let's assume $L_{EI}-$ energy intake loss

$$L_{EI} = \frac{1}{N} \sum_{i=1}^{N} \left(EI - \widehat{E}_I\right)^2 \tag{18}$$

The total loss due to the proposed VAE-GRN2 nutrient intake level children prediction system is shown in Eq. 19. Let's assume $L-$ loss.

$$L = L_{MC} + L_{KID} + L_{EI} + L_{Nutri} \tag{19}$$

User groups or clusters are formed using the nutrient intake level prediction dataset with a latent location structure. A proposed food recommendation system with different food programs significantly determines food preferences.

4 Results and Discussion

In this section, the performance of these methods is compared with the proposed VAE-GRN2 method to evaluate previous XGBoost, SSO-FNN, SmGAN, and SRCFA-NBGA methods under different conditions and constraints. The dataset's nutrient data collection functions allow adding records for various nutrient types. Furthermore, four metrics, such as the confusion matrix and multiple parameters, such as precision, accuracy, recall, F1 score, AUC-ROC curve, time complexity, and error rate, are utilized to evaluate the proposed technique.

Table 1. Simulation Parameter

Simulation	Variable
Dataset Name	Nutrients Dataset
No of Dataset	8790
Language	Python
Tool	Jupyter
Training	7,312
Testing	1478

Table 2. Performance of Sensitivity and Specificity

Methods	Sensitivity	Specificity
XGBoost	72	75
SSO-FNN	77	80
SmGAN	83	86
SRCFA-NBGB	87	89
VAE-GRNN	91	93

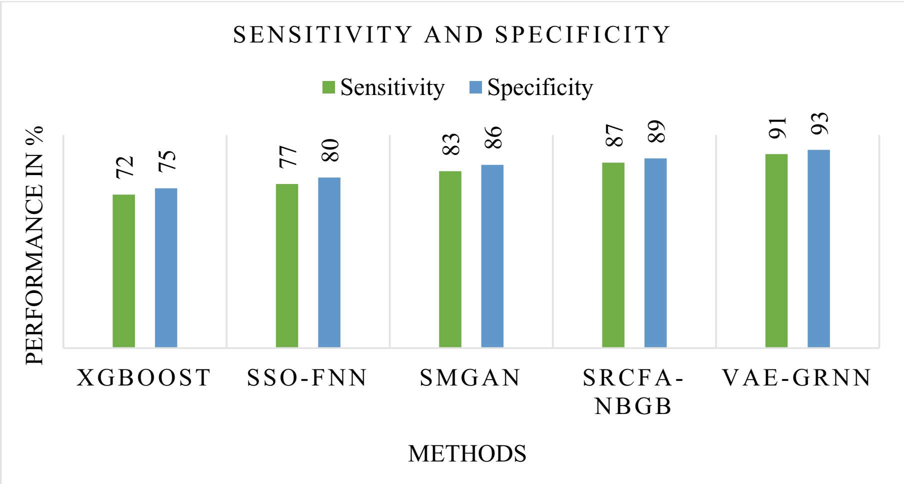

Fig. 3. Analysis of Sensitivity and Specificity

Simulated parameter variables can be used to train and test features of the nutrient dataset collected from Kaggle using train and test methods. In addition, the dataset, which has 8790 records, can be analyzed using the Jupyter tool in Python, as indicated in Table 1.

The proposed approach is compared with earlier techniques through sensitivity and specificity analysis in terms of the predictability of children's nutritional intake. Additionally, the efficacy of the proposed VAE-GRN2 approach has been demonstrated by a sensitivity rate of 91 percent in improving the nutritional intake of children. Likewise, the sensitivity of the proposed VAE-GRN2 approach of the nutritional intake of children is at 93 percent, as illustrated in Fig. 3 and Table 2.

The new technique will be compared with previous approaches in terms of precision analyses that aim to predict the nutritional needs of children. Additionally, the VAE-GRN2 model achieves a precision rate of 91 percent for this intake. Comparatively, other former approaches to this issue, such as XGBoost, SSO-FNN, SmGAN, and SRCFA-NBGB, demonstrate precision levels of 79%, 83%, 86%, and 88%, respectively, as shown in Fig. 4 and Table 3.

Table 3. Performance of Precision

No of Records	XGBoost	SSO-FNN	SmGAN	SRCFA-NBGB	VAE-GRN^2
2197	67	70	75	79	82
4,394	72	74	79	83	87
6,591	76	79	82	85	89
8,790	79	83	86	88	91

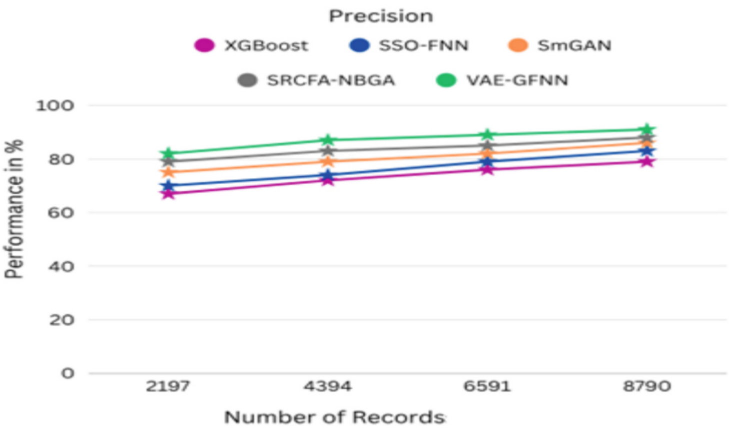

Fig. 4. Analysis of Precision

Table 4. Performance of Recall

No of Records	XGBoost	SSO-FNN	SmGAN	SRCFA-NBGB	VAE-GRN^2
2197	69	72	77	81	83
4,394	73	77	81	85	88
6,591	77	80	84	87	90
8,790	80	85	89	92	94

An overview of standard procedures was also conducted to compare the new method and determine its effectiveness. The analysis focused on comparing the recall of each technique regarding its potential to predict nutrient intake in children. The results of the study suggest the recall of each method, which are presented in Fig. 5 and Table 4. The earlier approaches in this comparison were XGBoost, SSO-FNN, SmGAN, and SRCFA-NBGB, which achieved corresponding recall rates of 79 percent for XGBoost, 83 percent for SSO-FNN, 86 percent for SmGAN, and 88 percent for SRCFA-NBGB.

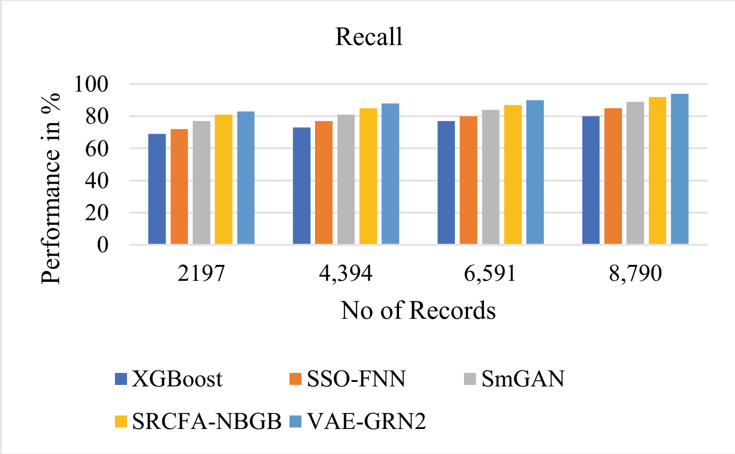

Fig. 5. Analysis of Recall

These statistics demonstrate the effectiveness of these developed methods in forecasting nutritional intake in children. The VAE-GRN2 achieved a recall score of 91% in predicting the nutrition consumed by children, outperforming other methods tested.

Table 5. Performance of F1-Score

No of Records	XGBoost	SSO-FNN	SmGAN	SRCFA-NBGB	VAE-GRN^2
2197	72	76	79	83	85
4,394	75	79	84	86	89
6,591	79	83	87	89	92
8,790	82	87	90	93	95

The accuracy of the newly developed method was compared to that of several previous techniques through a comparative analysis—the review aimed to evaluate the F1-score of each method in predicting nutrient intake in children. The results of the following analysis are presented in Fig. 6 and discussed in Table 5, highlighting the F1-scores obtained by each method. The strategies used in the comparison above were XGBoost, SSO-FNN, SmGAN, and SRCFA-NBGB, with F1-score rates of 82% for XGBoost, 87% for SSO-FNN, 90% for SmGAN, and 93% for SRCFA-NBGB. These figures suggest that the established methods are effective in predicting nutritional intake in children. The VAE-GRN2 achieved a 95 percent F1-score, which was used to indicate the nutritional intake of children compared to other tested methods.

This paper focused on evaluating the correctness of each belongingness in forecasting the dietary intake of children. The outcomes of the analysis undertaken indicate the accuracy scores of each method and are tabulated in Table 6 and displayed in Fig. 7. These statistics demonstrate that these already established methods are effective in predicting

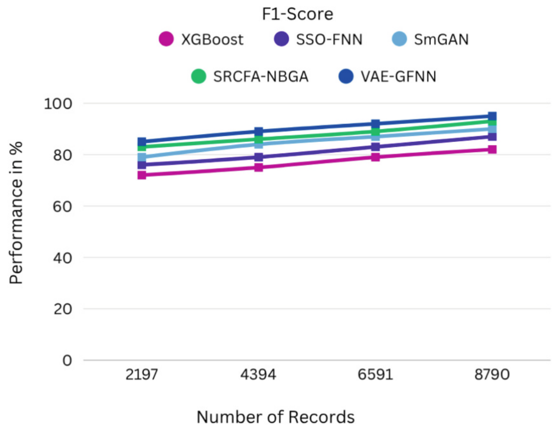

Fig. 6. Analysis of F1-Score

Table 6. Performance of Accuracy

No of Records	XGBoost	SSO-FNN	SmGAN	SRCFA-NBGB	VAE-GRN^2
2197	75	79	82	85	88
4,394	79	84	86	89	92
6,591	83	87	90	93	94
8,790	87	91	93	95	97

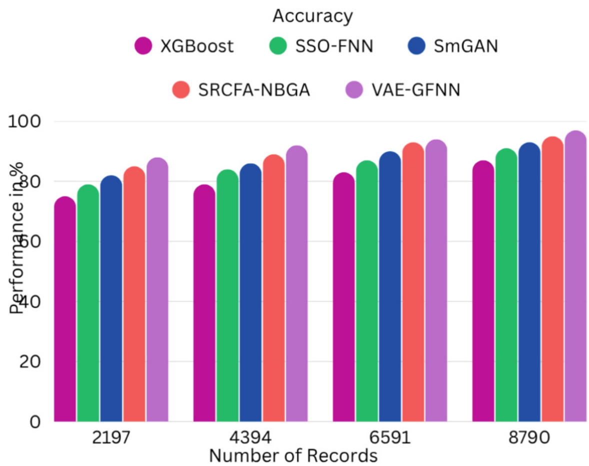

Fig. 7. Analysis of Accuracy

nutrient intake in children. In comparison to other methods of assessment, VAE-GRN2 was accurate in assessing the nutrient food intakes of children at 97%. In the above comparisons, XGBoost, SSO-FNN, SmGAN, and SRCFA-NBGB are the previous methods with an accuracy of 87%, 91%, 93%, and 95%, respectively.

Table 7. Performance of Time Complexity

No of Records	XGBoost	SSO-FNN	SmGAN	SRCFA-NBGB	VAE-GRN2
2197	49	47	44	40	35
4,394	44	43	41	37	31
6,591	41	40	36	33	23
8,790	37	38	34	27	18

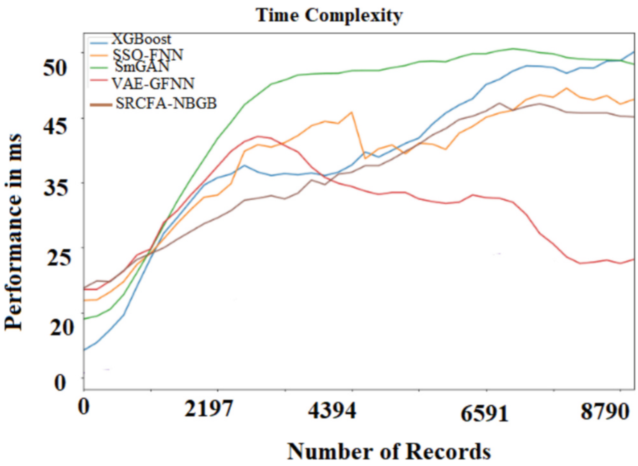

Fig. 8. Analysis of Time Complexity

They analyzed how accurately various methods of nutrient intake by children are predictive. The results of the tests are presented in Fig. 8 and summarized in Table 7, serving as an indicator of the time complexity of both methods. This data underscores the effectiveness of these established approaches in assessing children's nutrient intake. VAE-GRN2 achieved a time complexity of 18 ms, outperforming other assessment methods. In this comparison, the previous methods are XGBoost with 37 ms, SSO-FNN with 38 ms, SmGAN with 34 ms, and SRCFA-NBGB with 27 ms time complexity.

5 Conclusion

In conclusion, the proposed framework effectively addresses the challenges of malnutrition analysis in children by incorporating data-driven advanced deep learning and feature selection techniques. A new deep learning-based architecture, VAE-GRN2, is presented in the given research, which can help effectively predict caloric and nutrient values in children. The model is a combination of the VAE-GRN2 model, which effectively captures the temporal relationships in dietary data. Furthermore, the CSN algorithm was proposed to systematically detect and fix errors, duplicates, and missing values in the dataset to ensure high-quality input data. Moreover, we constructed the CNIN to determine the ratio of the effect of different nutrient profiles, which would provide further insights into the contribution of particular nutrients to the diet. Additionally, we adopted the DVSGFS method to increase model efficiency and performance, which will allow us to select the most informative features to predict nutrients. The offered framework shows great potential in the process of assisting with the nutritional monitoring and personalized diet planning, as well as interventions concerning the child nutrition at the population level. Finally, enhance predictive power to determine the status of children's diet using the VAE-GRN2 model.

All of this leads to the conclusion that the proposed innovative advances made in this research come together for a highly accurate and efficient systematic approach to accurately define a child's dietary behavior with a full complement of nutrition policies and guidelines accomplished hence finalities to let of 97% across all key performance measures of successful pedagogical methodology. Precision, recall, F1-score, and time Complexity present strong potential to change even modest healthcare systems if child nutrition monitoring and discerning decision support methodological frameworks could become normalized.

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