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A Child Dietary Prescription Model using Artificial Neural Network and Fuzzy Logic

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ABSTRACT:

In developing countries, malnutrition in children is a persistent problem that is of national concern because of the high poverty rate and ignorance of parents on impact of proper nutrition on children. Malnutrition is attributed to the deficiencies or excesses nutrient intake, that is, imbalance of essential. Malnutrition in children often result to poor growth, frequent sickness and death. Hence, remedying malnutrition problem in children is very important because present days children are the labour force that will execute the policies of next generation government in all sectors and so it is important that they are healthy. Decision support systems can provide sensitization, diagnosis and quick prescription to medical practitioners and parents based on observable symptoms from a child patient. Advances in the field of artificial intelligence, for the past decades have proven proficient in the provision of viable solutions to real world problems. These advances have prompted this study to harness the viabilities of the artificial neural network and the fuzzy logic to develop a dietary prescription model for children. The outcomes of this study underscore the potential of this method in tailoring dietary recommendations to individual child nutritional needs. This study's result showed accuracy of 93% and an AUC score of 98%.

Keywords: Malnutrition, deficiencies, artificial intelligence, fuzzy logic, dietary, accuracy.

1. INTRODUCTION

Malnutrition is the deficiencies or excesses in nutrient intake, imbalance of essential nutrients or impaired nutrient utilization. It has proven to be a universal issue that no country in the world can afford to overlook [1];[2]. A survey conducted by the World Health Organization revealed that as of the year 2022, about 45% of mortality among children under five years of age are linked to undernutrition and these mortalities are mostly prevalent in low and middle-income countries with increasing growth rates of childhood overweight and obesity [1]. Consequence of malnutrition includes stunted growth, poor cognitive development, a lowered performance in education, and low productivity in adulthood due to imbalance dieting plans - all contributing to economic losses estimated to account for as much as 11 percent of the Gross Domestic Product (GDP) [3]. Despite these attendant dangerous consequences, dietary recommendation is still an unaided task, relying on the limited medical practitioners' knowledge, acumens, and presumed ability to conduct an unbiased recommendation for children's dietary problems [4].

However, considering the advances in technology and knowledge, it's woe to solely rely on medical personnel to recommend nutritional schedules as nutrition-related diseases can considerably contribute to many different health-related problems and can impact several segments of the population within a finite time frame [5]. Thus, promoting balanced diet plans is therefore pivotal as such this study proposed the integration of an artificial neural network and rule-based fuzzy logic to develop a smart device decision support system for children's diet. These artificial intelligence methods have proven to be supplemental tools to accelerate health care and medical decisions delivery (in particular dietary recommendation) with eliminated errors, and cost-effectiveness [6]. Existing researches including [7] have applied the concept of fuzzy logic to develop dietary decision support systems. But their work has a drawback of non-adaptivity, this is because fuzzy logic decisions are static to its inference engine. To remedy this challenge, this work uses the integration of deep learning and fuzzy logic method to improve the existing methods as an attempt to develop an adaptive decision support model.

2. LITERATURE REVIEW

AI is broadly defined as the application of computers to independently or semi-independently perform functions that mimic human intellect [8]. Machine learning, a subset of AI, involves computer algorithms that process and learn from data without requiring explicit programming to define each step. Deep learning is a further subset of AI and machine learning that involves the use of multi-layered neural networks ("deep learning") to permit far more complex analyses [8]. The AI system can nonetheless improve ("learn") over time as it gets exposed to more data. Training can be performed in a supervised, semi-supervised, or unsupervised manner. Supervised learning involves the use of labeled data that "teach" the system about the meaning and relationships within the data, such as labeling data outcomes to allow the system to identify shared and unique features inherent in each data output label [9]; [10]. Unsupervised learning involves the processing of data without human intervention, such as pattern recognition of unlabeled data for clustering, anomaly detection, or reduction of complex data [11].

2.1 Artificial Neural Network (ANN)

Artificial neural network (ANN) model involves computations and mathematics, which simulates the biological neural network. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron, the inputs are weighted what means that every input value is multiplied with individual weight. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron, the sum of previously weighted inputs and bias is passed through activation function that is also called transfer function [12]; [13].

A neuron compares the computed weighted sum of its n input signals $X_j = 1, 2 \ldots, n$ with certain preset thresholds. An output of 1 is generated if the threshold is exceeded, otherwise the output is simply 0 [14]. The activation functions that determine the comparison thresholds include linear, sigmoid, and Gaussian functions; the sigmoid is however the most commonly used function [14]. Mathematically, the sum of the weighted input of a neuron j is expressed in equation 1.

$$net_j = \sum_{j=1}^{n} w_j x_j \qquad (1)$$

While the neuron's output, y which is a function of its weighted input is expressed in equation 2.

$$y = f(net_j) \qquad (2)$$

Feed forward neural network architecture consists of an input layer, output layer and hidden layers if required. The network is fed input data through the input layer; the numbers of neurons (nodes) which make up the input layer are representative of the independent variables from which the dependent variable will be determined. Where hidden layers are used, the number of nodes embedded in the hidden layer is usually decided by trial and error. Hidden nodes receive input values; calculate the input values' weighted sum and then, based on the transfer function selected, squeezes the values into a limited range [12]. The squeezed values then serve as input to the output nodes where the same process is again repeated. Figure 1 illustrates a simple ANN model.

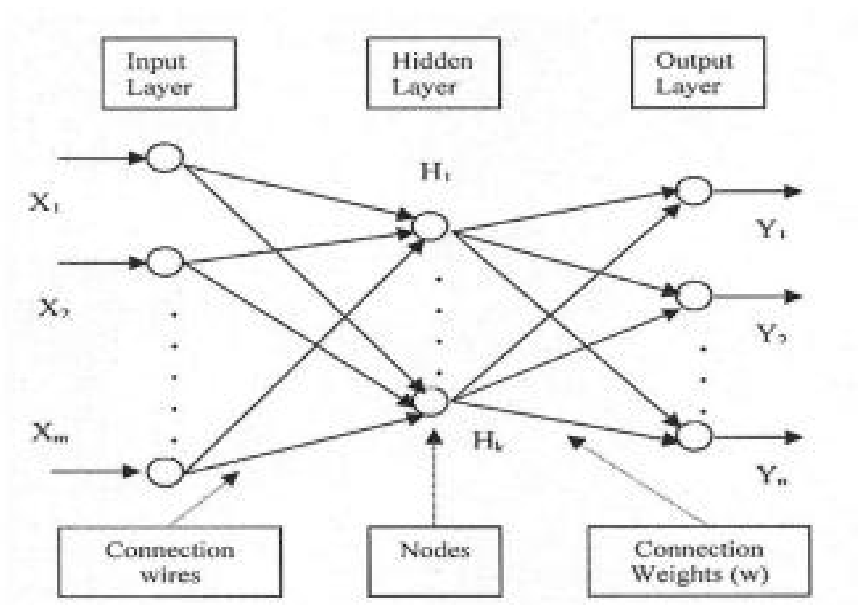

Figure 1: Artificial Neural Network Architecture (source: [12]).

A neural network is trained to minimize output error by adjusting network weights and biases. This it does by using one of several learning algorithms. The back propagation learning algorithm with feed forward network architecture is considered most suited for predictions [15]. Inputs are sent forward to hidden and output nodes while errors are propagated backwards through the network. Using the back propagation algorithm, a network is trained with an input and its corresponding output to a point where a function and an input becomes associated with a specific output. Where properly trained, back propagation networks usually give reasonably accurate responses when presented with new inputs. The training of the network through adjustment of weights is usually a trial by error process, since no single algorithm suits all applications [15].

2.2 Fuzzy Logic

Fuzzy logic was created as a result of attempts to model human thinking, experience and intuition in the decision-making process based on inaccurate data. It is suitable for expressing vagueness and uncertainty [16]. A fuzzy set *A* of set *X* can be defined as a set of ordered pairs given in the equation 3:

$$A = x, \mu_A\, xx \; \in X, 0 \leq \mu_A x \leq 1 \qquad (3)$$

Where *X* is a set of considerations in which a fuzzy set *A* is defined and $\mu_A (x)$ is a membership function of the element x of the set *A*. The fuzzy logic introduces the notion of a membership function which is interpreted as a degree of truthfulness of the claim, and thus it is closely related to problems and events from everyday life [16]. Each fuzzy set is completely determined by its membership function which represents the degree of belonging of the elements x to the fuzzy set *A*, which is represented in equation 4.

$$\mu_A x: X \; \rightarrow 0, 1 \qquad (4)$$

Fuzzy numbers are defined as convex normalised fuzzy sets. A fuzzy set is normalised if at least one element belongs to this set with degree of belonging 1. According to the fuzzy theory, the choice of the membership function, i.e., the form of the function and the size of the confidence interval, is most often performed on the basis of subjective assessment or experience. The most common forms of the membership function are: triangular, trapezoidal, Gaussian, and bell-shaped [17]. The fuzzy logic basic methodology is shown Figure 2;

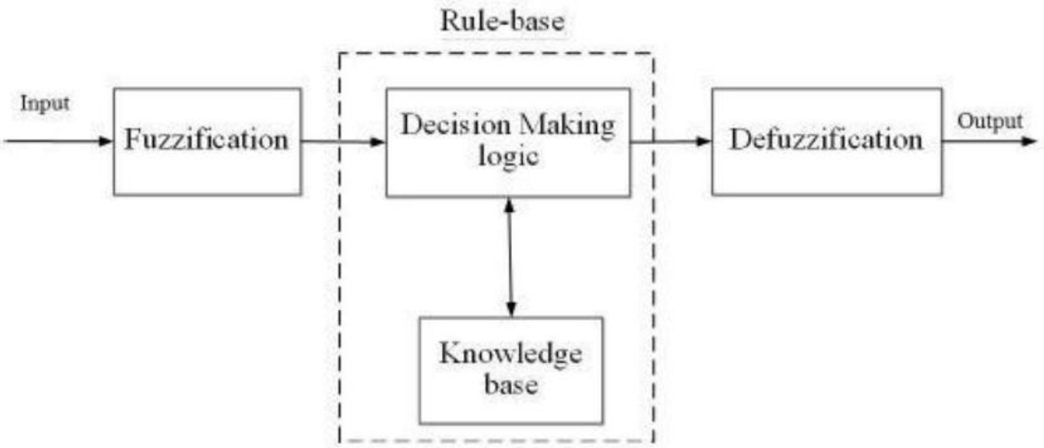

Figure 2: Basic Fuzzy Logic Methodology (source: [17])

2.3 Neuro-fuzzy System

Neuro-fuzzy System, is the combination of ANN with fuzzy systems, usually have the advantage of allowing an easy translation of the final system into a set of if-then rules, and the fuzzy system can be viewed as a neural network structure with knowledge distributed throughout connection strengths. The network learns in two main phases. In the forward phase of the learning algorithm, consequent parameters identify the least squares estimate [13]. In the backward phase, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm. Learning or training phase of the neural network is a process to determine parameter values to sufficiently fit the training data The main benefit of this combined method is quick convergence, since it diminishes the search space dimensions of the backpropagation method [13].

2.4. Related Survey

Krishna *et al.,* [19] carried out comparative analysis of four machine learning models for predicting malnutrition in children dataset from UNICEF. Their developed models were; Support Vector Machine (SVM), KNN, logistic regression, Naïve Bayes, and a two-layer neural network, which were employed to identify malnutrition in children. Among these models, logistic regression demonstrates superior accuracy compared to the other algorithms. Logistic Regression was able to accurately classify malnourished children based on the scatter plot of WAZ and LAZ, with an accuracy of 95.9% for WAZ and 94.8% for LAZ. Where WAZ and LAZ were the feature indicators. The indicators used for determining malnutrition among others were; WAZ (underweight), HAZ (stunting), and WHZ (emaciation). These indicators provide information about a child's growth and body composition. Merajul *et al.,* [20] made use of 15,464 records of the dataset from the Bangladesh Demographic and Health Survey. Their study made use of

Multinomial Logistic Regression (MLR) for feature extraction and implemented five Machine Learning-based algorithms; Naïve Bayes, support vector machine, decision tree, artificial neural network, and random forest (RF) for predicting malnourished women and evaluating their performances using accuracy and area under the curve (AUC). The comparative evaluations of the machine learning models showed that RF-based classifier provides 81.4% accuracy and 0.837 AUC for underweight and 82.4% accuracy and 0.853 AUC for overweight/obese. Catherine *et al.,* [21] investigate the use of weight and length velocities vs attained growth measures to predict stunting, wasting, and underweight at age 2 years. The study's used Linear and Logistic Regression models to predict malnutrition at 2 years of age with growth velocity z scores at 0-3, 0-6, 3-6, 6-9, 6-12, and 9-12 months, using attained growth as indicators. The research result showed that at age 2 years, 4% of the children were wasted, 13% underweight, and 21% stunted. Children who were malnourished at age 2 years had lower mean growth z scores already at birth and throughout the study period. Maximum AUC values for weight and length velocity were 70-84. Mosharaf *et al.,* [22] developed a regression model to discover the risk factors of underweight and overweight among women in Bangladesh. Their study developed the chi-square test (χ^2) and logistic regression model to this effect. The study concluded that rural women in Bangladesh had a significantly positive association with being underweight (OR = 1.127, 95%CI = 0.983–1.292) and overweight (OR = .810, 95%CI = 0.682–0.962).

3. METHODOLOGY

The entire model architecture consists of five layers, namely fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. With input/output data for given set of parameters, the ANN-FL models operates as a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using backpropagation algorithm. The main objective of the ANN-FL is to determine the optimum values of the equivalent fuzzy inference system parameters by applying a learning algorithm. The parameter optimization is done in such a way during the training session that the error between the target and the actual output is minimized. The parameter set of an adaptive network allows fuzzy systems to learn from the data they are modeling. This paper used two inputs V1 and V2 to generate one output f. A first order Takagi, Sugeno and Kang (TSK) fuzzy inference system containing two rules:

Rule 1: If (v is v_1) and (d is D1) then $f_1 = p_1v + q_1d + r_1$

Rule 2: If (v is v_2) and (d is D2) then $f_2 = p_2v + q_2d + r_2$

Where p_1, p_2, q_1 , q_2 , r_1 and r_2 are linear parameters and v_1, v_2, D_1 and D_2 are non-linear parameters, in which V1 and D1 are the membership functions of the ANN-FL (antecedent). p_1, q_1 , r_1 are the consequent parameters. To reflect adaptive capabilities, this work uses both circle and square. A circle indicates fixed node whereas square indicates adaptive node. The Developed child dietary prescription model using ANN-FL is shown in Figure 3

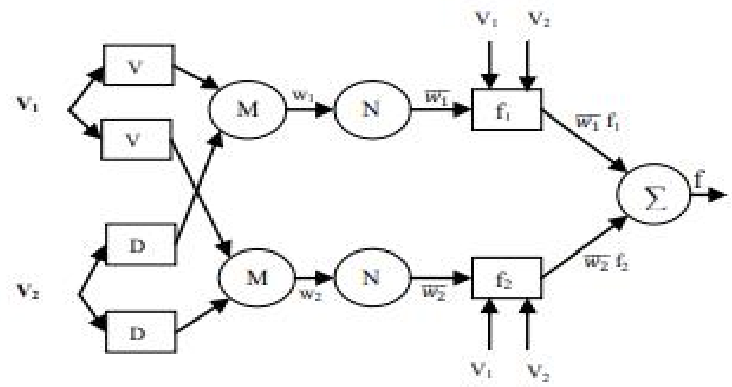

Figure 3: Architecture of the Developed ANN-FL Model for Child Dietary Prescription

The layers of the ANN-FL for the Child Dietary Prescription model are described as follows;

Layer 1

Each input node i in this layer is an adaptive node which produce membership grade of linguistic label. It is a fuzzy layer, in which v and d are input of system. $O_{1,i}$ is the output of the i[th] node of layer l. Each adaptive node is a square node with square function represented using Equation 5 and 6.

$$O_{1,i} = \mu_{v,i}(v) for\ i = 1, 2 \quad (5)$$

$$O_{1,j} = \mu_{d,j}(v) for\ j = 1, 2 \quad (6)$$

Where $O_{1,i}$ and $O_{1,j}$ denote output function and $\mu v,i$ and $\mu_{d,j}$ denote membership function.

This study choose triangular membership function, $\mu_{v,i}(v)$ is given by equation 7:

$$\mu_{v,i}(v) = \max\left[\min\left(\frac{v-a_i}{b_i-a_i}, \frac{c_i-v}{c_i-b_i}\right), 0\right] \quad (7)$$

Where {a_i, b_i, ci} are the parameter of triangular membership function.

Layer 2

This layer checks weights of each membership function, it receives input values vi from first layer and acts as a membership function to represent fuzzy sets of respective input variables. Every node in this layer is fixed node labeled with M and output is calculated via product of all incoming signals. This is called the firing strength. The output in this layer is represented using Equation 8:

$$O_{2,\,i} = w_i = \mu_{v,\,i}\,(v).\,\mu_{D,\,j}\,(d), i = 1, 2. \qquad (8)$$

Layer 3

Every node in this layer is fixed marked with circle labeled with N, indicating normalization to the firing strength from previous layer. This layer performs pre-condition matching of fuzzy rules, i.e. they compute activation level of each rule, the number of layers being equal to number of fuzzy rules. The i[th] node in this layer calculates ratio of i[th] rule"s strength to the sum of all rules firing strength. The output of this layer is expressed as wi using Equation 9.

$$O_{3,\,1} = \overline{w_i} = \frac{w_i}{w_1+w_2}, i = 1, 2 \qquad (9)$$

The outputs of this layer are referred to as normalized firing strengths.

Layer 4

This layer provides output values y, resulting from the inference of rules. The resultant output is simply a product of normalized firing rule strength and first order polynomial. A total of nine fuzzy rules were used. Weighted output of rule is represented by node function as depicted in equation 10.

$$O_{4,\,i} = \overline{w_i}fi = \overline{w_i}\,(\,p_{iv} + q_{id} + r_i\,)\,, i = 1, 2 \qquad (10)$$

Where $O_{4,\,i}$ represents layer 4 output. In this layer, $p_i\,, q_i\; and\; r_i$ are linear parameter.

Layer 5

This layer is called output layer which sums up all the inputs coming from layer 4 and transforms fuzzy classification results into crisp values. This layer consists of single fixed node labeled as "∑". This node computes summation of all incoming signals and it is calculated using Equation 11.

$$O_{5,\,i} = \sum_i \overline{w}_i\, f_i = \frac{\sum_i w_i\, f_i}{w_1+w_2}, i = 1, 2 \qquad (11)$$

The Artificial Neural Network and Fuzzy logic (ANN-FL) model for Child dietary prescription made use of dataset obtained from Benue State National Library on global, regional, and national prevalence of overweight and obesity in children and adults from 1980-2019 and, nutritional health record from the General Hospital Wukari, Nigeria, was collected on children of age 1-10. The attributes in the datasets includes type of food, nutritional contents, recommended quantity consumable per day, weight, height, body mass index, and weight status for each child's gender etc. These were the inputs to the ANN-FL model. The statistic description of the dataset revealed that it contains 10000 malnutrition patient records of children between age 1-10. A more elaborate description is illustrated in Figure 4 and 5; where the 'min' signifies the minimum floating value within a given data column, 'std' denotes the standard deviation of the dataset specific to a labeled column, and 'max' articulates the maximum values observed in the corresponding column. Each column is associated with its distinctive values for the respective descriptive statistics, encompassing count, mean, standard deviation, minimum, maximum, and scale data intervals at 25, 50, and 75 percentiles, thereby contributing to a comprehensive analytical. To implement the ANN-FL model for dietary prescription for children, this study made use of Phyton programming, Visual Studio Code as the development environment, Java Software Development Kit (SDK) as a library for incorporating source code and windows operating system of 4GB Random Access Memory (RAM), and 500GB Read Only Memory (ROM). The algorithm for the operation of the developed model is shown as follows;

```
In [57]: df.head()
Out[57]:
```

	Toddler ID	Age(month)	Gender	Weight (kg)	Height (cm)	BMI(kg/m2)	BMR(kcal/kg/d)	Energy (kcal/d)	Protein(g/d)	Fat(g/d)	...	Ascorbic acid(mg/d)	Dietary folate(mg/d)	Magnesium(mg/d)	Calc
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	
1	Td001	2.0	male	5.4	62.0	14.0	54.0	531.2	0.4	2.1	...	25.0	25.0	30.0	
2	Td002	11.0	male	9.0	71.0	17.0	51.0	11.0	2.9	19.0	...	25.0	25.0	45.0	
3	Td003	36.0	male	12.9	86.0	16.9	57.0	1060.0	16.7	17.0	...	40.0	80.0	50.0	
4	Td004	60.0	female	18.0	115.0	13.6	48.0	1350.0	20.1	25.0	...	40.0	100.0	70.0	

5 rows × 27 columns

Figure 4: Dataset Visualization

```
df.describe()
```

	Age(month)	Weight (kg)	Height (cm)	BMI(kg/m2)	BMR(kcal/kg/d)	Energy (kcal/d)	Protein(g/d)	Fat(g/d)	Vit B12(mg/d)	Riboflavin(mg/d)	equi
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	46.020100	17.184310	97.252700	19.492900	46.62790	1213.203660	16.451568	25.258022	3346.682884	0.585639	
std	39.440434	9.946689	28.363006	23.179777	7.37008	627.363563	14.291804	6.719886	1360.132577	0.253905	
min	1.000000	5.400000	60.000000	1.400000	32.00000	11.000000	0.200000	1.300000	0.000000	0.000000	
25%	9.000000	8.000000	71.000000	13.600000	44.00000	600.000000	1.560000	18.000000	2600.000000	0.300000	
50%	35.000000	12.900000	86.000000	16.900000	48.00000	1060.000000	16.000000	25.000000	3200.000000	0.690000	
75%	76.000000	24.300000	115.000000	17.900000	54.00000	1689.000000	29.000000	30.000000	4800.000000	0.700000	
max	130.000000	35.000000	144.000000	192.000000	57.00000	2190.000000	40.000000	41.200000	4800.000000	1.300000	

Figure 5: Dataset Statistical Description

The first phase of the model inculcates the application of the decision-making process using the fuzzy logic approach whereas, the second phase involves the amalgamation of the Artificial Neural Network approach to the decision-making process. Some of the key steps also incorporated involve a data preparation procedure that entails the removal of unwanted characters, and missing values, and also using the information gain algorithm as a feature selection technique before performing data encoding and scaling; secondly, feeding the cleansed, scaled, and trained dataset to the developed Artificial Neural Network – Fuzzy Logic (ANN-FL) model based on the ratio of 70:30 training to test proportions and performance evaluation of the model using precision, recall, accuracy, and f1-score. The model was implemented using the Python programming language, together with many third-party libraries like NumPy, Matplotlib, Pandas, TensorFlow, and Sklearn. The developed model operation is explained in Algorithm 1.

Algorithm 1: Artificial Neural Network and Fuzzy Logic Algorithm for Child Dietary Prescription Model

 # Define function for fuzzification in the first layer function fuzzified (input data):

- *Triangulation technique with equally spaced membership functions*
- *Create neurons with activation functions as membership functions*
- *Probabilistic approach to limit the relation of neurons*
- *Return membership degrees associated with input values*

 # Define function for aggregation and rule extraction in the second layer function aggregate_and_prune (fuzzy outputs):

- Logical neurons type III for aggregation

- Extract fuzzy rules from the database

- Pruning approach using f-scores to filter less-needed rules

- Return aggregated and pruned outputs

 # Define function for binary pattern classification in the third layer

function classify_binary_pattern (aggregated outputs):

- *Single artificial neuron for binary pattern classification*
- *Weights obtained through mean squares parameterization techniques*
- *Return the output of the model*

 # Main function for the ANN-FL model

function ann_fl_model(input_data):

 # First layer - Fuzzification

fuzzy_outputs = fuzzify(input_data)

 # Second layer - Aggregation and Pruning

aggregated_outputs = aggregate_and_prune(fuzzy_outputs)

 # Third layer - Binary Pattern Classification

```
    model_output = classify_binary_pattern(aggregated_outputs)

    # Return the final output of the ANN-FL model

    return model_output

# Call the main function with input data

input_data = read_input_data()

output_result = ann_fl_model(input_data)

display_output(output_result)
```

4. RESULTS AND DISCUSSION

The Child Dietary Prescription Model was configured with specific parameter settings, as detailed in Table 1. These settings play a critical role in influencing the learning process and overall performance of the model. The "Batch Size" parameter is set to 32, indicating the number of training samples utilized in each iteration. A batch size of 32 strikes a balance between computational efficiency and model accuracy during the training phase. The "Max epochs" parameter is assigned a value of 50, representing the maximum number of complete passes through the entire training dataset during the training process. This limitation helps prevent overfitting and ensures that the model converges to an optimal state within a reasonable number of iterations. The "Initial learn rate" is set to 0.001, determining the step size at the beginning of the training. This parameter influences the rate at which the model adapts to the training data, with a lower value indicating a more cautious learning approach. The choice of "Optimizer" is Adam, a popular optimization algorithm in machine learning. Adam combines the benefits of two other optimization methods, namely RMSprop and momentum, providing an efficient and adaptive approach to adjusting the model's weights.

The "Drop" parameter, set at 0.5, signifies the dropout rate, which represents the proportion of neural network units that are randomly omitted during training. This regularization technique helps prevent overfitting by introducing a degree of randomness in the learning process. For the "Loss" function, the mean square error was employed. This loss function is suitable for scenarios where the classification task involves multiple classes, as in the case of the Toddler Malnutrition System. It computes the cross-entropy loss between true class labels and predicted probabilities. Lastly, the "Memberships" parameter is set to 2, indicating the number of fuzzy membership functions employed in the ANNFIS model. The selection of an appropriate number of membership functions is crucial for capturing the underlying patterns in the data and enhancing the interpretability of the fuzzy inference system.

Table 1: ANN-FL Algorithm's Parameter Settings for Child Dietary

Parameter	**Value**
Batch Size	32
Max epochs	50
Initial learn rate	0.001
Optimizer	Adam
Drop	0.5
Loss	mean square error
Member	2

The Child Dietary Prescription Model was implemented using the hybrid of Artificial Neural Networks and Fuzzy Logic (ANN-FL). Analytical, the ANN-FL model underwent training with specific hyperparameters, including 50 epochs, a batch size of 32, and a learning rate of 0.001. The resulting accuracy achieved by the model is 93%, indicating a high level of success in the model's ability to make correct predictions. Essentially, this implies that the model, combining the power of Artificial Neural Networks and Fuzzy Logic, effectively learned and generalized patterns from the training data.

The metrics used to evaluate the child dietary prescription model classification capability includes precision, recall, F1-score and Area Under the Curve (AUC). The model has a 0.93 precision for class 0 (not mal-nutrition), indicating that 93% of instances predicted as class 0 were correct. For class 1 (mal-nutrition), the precision is also 0.93, meaning that 93% of instances predicted as class 1 were correct. Considering the recall, for class 0, the recall is 0.92, indicating that 92% of actual class 0 instances were correctly predicted. For class 1, the recall is 0.93, meaning that 93% of actual class 1 instances were correctly predicted. Lastly, for the metric F1-score, the model for both classes 0 and 1 has an F1-score of 0.93. In summary, the developed child dietary prescription model showed strong performance across precision, recall, and F1-score for both classes. The overall accuracy of 92.83% indicates that the model is effective in making accurate predictions on the given dataset. These are shown in Figure 6.

```
 ANFIS model Accuracy: 92.83%
48/48 [==============================] - 2s 29ms/step
ANFIS Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.92      0.93       747
           1       0.93      0.93      0.93       760

    accuracy                           0.93      1507
   macro avg       0.93      0.93      0.93      1507
weighted avg       0.93      0.93      0.93      1507
```

Figure 6: Classification Performance Metric for the Child Dietary Prescription Model

Also, the Receiver Operating Characteristic (ROC) curve, which is a graphical representation for demonstrating the classification performance of a model was also used to evaluate the developed Child dietary Prescription Model. that illustrates the performance of the toddler nutrition model across different threshold settings. The Area Under the Curve (AUC) is a metric associated with the ROC curve, providing a summary measure of the model's ability to discriminate between the two classes. The AUC value, ranging from 0 to 1, represents the probability that the model will correctly rank a randomly chosen positive instance higher than a randomly chosen negative instance. This high AUC value suggests that the ANN-FL model has a strong ability to distinguish between the two classes. The AUC result for the developed model is With an AUC of 98%. Hence, the model is effective at assigning higher predicted probabilities to positive instances than to negative instances. This is shown in Figure 7.

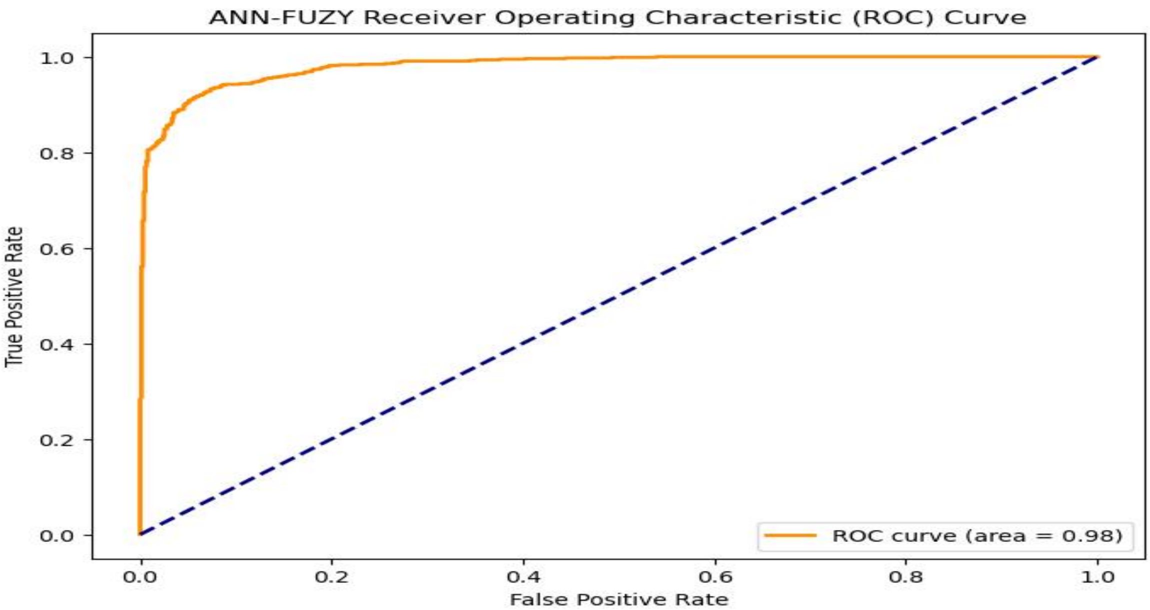

Figure 7: ROC for the Child Dietary Prescription Model

5. CONCLUSION AND RECOMMENDATION

In conclusion, this study has integrated Artificial Neural Network (ANN) and Fuzzy Logic (ANN-FL) methods to develop a child dietary prescription model. The model function to aid nutritionist and medical doctors in early diagnosis of malnutrition and timely suitable dietary recommendation for malnutrition patient of age 1 to age 10. The choice of integrating ANN and Fuzzy logic method for this study was motivated by its ability to handle the non-linearity and uncertainty present in nutritional data, offering a more nuanced approach compared to traditional statistical methods.

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