A Proposed Algorithm Based on Artificial Intelligence to Optimize the Ratio of Food Combinations on a Meal Plate

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Abstract. Background. The *Pedoman Gizi Seimbang* (Balance Nutrition Guideline, PGS) program was already mandated by the Indonesian Health Ministry as a national daily intake recommendation. The government uses the *Isi Piringku* (My Plate, IP) program to improve the program further. However, the food combination ratio was chosen arbitrarily by the government. **Objective**. Our proposed approaches to using artificial intelligence to calculate a balanced food ratio are outlined in this article. **Designs**. This is developmental and experimental research. **Data Source**. We have used the 2017 edition of *Tabel Komposisi Pangan Indonesia* (Indonesia Food Composition Table, TKPI) for reference data. **Methods**. A straightforward proof of concept for our methods has been created. As our training objective, we have chosen to adhere to the national daily intake recommendation. The input data are rearranged into five groups according to my plate program from the TKPI. The daily meal training data were then created by combining the two data. To determine the ideal food-to-drink ratio, we must infer from the training data. **Results**. Using meals derived using the conventional method, we have compared nutrition values and created a sample set meal ratio using our tools. In total, 21 macronutrients and micronutrients are evaluated. **Conclusions**. The creation of mobile-based tools for simple food ratio implementation would be part of the plan. In addition, the researchers ought to think about carrying out an experimental trial to contrast the efficacy of this strategy with that of conventional strategies in community settings.

Keywords: Algorithm · Artificial Intelligence · Food Combinations Ratio · Meal Plate

A. Suraya et al. (Eds.): WCHSS 2022, AHSR 63, pp. 110–118, 2023.
https://doi.org/10.2991/978-94-6463-186-9_14

1 Introduction

Every nation publishes daily food intake guidelines for its citizens [1, 2]. Indonesia itself furnishes this norm with PGS [3, 4]. Non-communicable cardiovascular disease-related diseases continue to rise due to diet and obesity [5, 6]. Even though life expectancy is increasing, it does not mean living in a healthy state [7]. One of the leading causes of death from disease is cardiovascular disease, followed by respiratory diseases and cancer [8–13].

Pearce et al. enumerate four significant flaws in the global strategy for dealing with non-communicable diseases. Inadequate understanding of the primary factors that contribute to non-communicable diseases (NCDs). Too little focus on the cardiovascular, diabetes, cancer and chronic respiratory diseases target population. Inattention to “structural” NCD determinants, such as the environment, Loss of significance of coordinated medical care for NCDs [14]. The wrong diet still plays a significant role in cardiovascular disease [15, 16], and during a pandemic, it gets worse [17]. To reduce these risks, it is essential to improve families’ knowledge, schools, and health service capabilities [18–24].

The PGS ratio of food intake is not supported by any evidence, according to the authors. It is arbitrary to determine the food ratios. As a result, it is necessary to evaluate the ratio of food components on dinner plates.

Our proposed approaches to using artificial intelligence to calculate a balanced food ratio are outlined in this article. As part of efforts to create an automated food nutrition recommendation system, this research plays a role. This effort, which will be linked to our other research [25–27], addresses the risk of non-communicable diseases.

2 Methods

As a starting point, we obtained the 2017 edition of the national food composition table, TKPI. Following that, we divide them into 13 food groups, as shown in the table [28]. According to pedoman gizi seimbang, we further group them into five categories: staple foods, side dishes, vegetables, fruits, and others. Pedoman gizi seimbang is also used as a reference for the recommended daily intake [3, 4]. PGS suggested that we use the fifth group in the calculation, but we did not.

To use it as training data, we have combined the two sets of data. The traditional approach, the balanced energy approach, the restricted balanced energy approach, the balanced macronutrient approach, and the balanced nutrient approach are all compared to various scenarios. In PGS, we described the conventional strategy as a standard 2:1:1:2 edible mass ratio. A hypothetical ratio in which the anticipated energy intake of each group is equal is known as the balanced energy approach. A balanced energy approach is the restricted balanced energy approach. We have, however, limited it so that no portion will occupy more than half of the meal plate. A hypothetical ratio is what the balanced macronutrient approach is. The standard deviation between protein, lipid, carbohydrate, and fibre requirement conformance is minimized by this strategy. The previous strategy is similar to the balanced nutrient approach. The strategy is to minimize the requirement conformance standard deviation for each nutrient, as described in TKPI. For both the

Balanced macronutrient approach and the Balanced nutrient approach, we used equation (1). We have restricted the algorithm to ensure that the calculated result for each component never falls below 5 per cent.

```
void findBestRatio()
{
   //find most balanced meal ratio
   for each ratio
   {
      calculateEachNutrient();
      calculateNutrientBalance();
      updateBestNutrientBalance();
   }
}
```
(1)

A straightforward 600-kilocalorie meal is our benchmark. Additionally, there is no restriction on total meal weight. Each output nutrient's compliance with the Indonesian National Daily Recommended Intake has been compared. We have used LibreOffice Calc (The Document Foundation, Germany) and Qt SDK (Digia Plc., Finland) for numerical calculation.

3 Results

Table 1 shows the TKPI. Table 2 shows the Indonesian national daily recommended intake. Figure 1 depicts each resultant food ratio, and Fig. 2 depicts each resultant conformance.

Table 1. Truncated and summarised version of Table Komposisi Pangan Indonesia [28].

Code	Group	n	Water (g)	Energy (kcal)	Protein (g)	Lipid (g)	Carb (g)	Fibre (g)	Ash (g)
A	Cereals	135	36.34	279.28	4.96	5.67	51.47	2.27	0.99
B	Tubers	109	38.89	262.93	1.65	4.66	52.90	3.17	1.27
C	Legumes	138	31.21	320.38	16.22	13.53	36.58	5.85	4.36
D	Vegetables	227	84.67	61.27	3.11	1.68	9.22	3.16	1.34
E	Fruits	127	73.56	106.11	1.31	1.46	22.85	3.49	1.06
F	Meat and Poultry	122	59.57	216.79	19.12	12.64	6.21	0.35	2.18
G	Seafoods	179	60.42	171.91	21.75	6.07	7.02	0.09	5.19
H	Eggs	18	58.44	232.17	13.38	16.54	7.14	0.00	1.28
J	Milks	17	60.58	193.71	10.41	9.02	17.78	0.00	2.20
K	Oils	18	19.54	681.83	2.14	74.37	3.03	0.47	0.97
M	Confectionary	18	18.94	319.89	7.14	7.53	59.00	5.16	3.89
N	Condiments	37	55.36	181.70	8.46	5.71	24.56	4.16	5.44
Q	Drinks	1	95.50	17.00	0.20	0.10	3.80	0.00	0.40

Table 2. A simplified version of the Indonesian Daily Recommended Intake [3, 4]

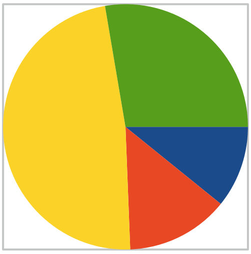
Water (g)	1850
Energy (kcal)	2000
Protein (g)	50
Lipid (g)	65
Carb (g)	300
Fibre (g)	28
Calcium (mg)	1200
Phosphorus (mg)	1250
Iron (mg)	8
Natrium (mg)	1300
Kalium (mg)	3900
Cuprum (mg)	700
Zinc (mg)	8
Retinol (mg)	600
Thiamine (mg)	1.1
Riboflavine (mg)	1.3
Niacine (mg)	12
Vitamin C (mg)	50

4 Discussions

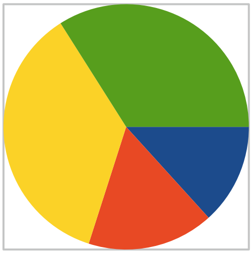
Few studies support the mandated ratio of the PGS [3, 4]. While applications of artificial intelligence for food intake are emerging, this manuscript may be one of the first [29–34]. This research may be among the earliest attempts to elaborate on the effect of food ratio on nutrient composition inside an artificial intelligence approach. This study may be one of the earliest attempts to use artificial intelligence to investigate how food ratio affects nutrient composition.

Based on Fig. 1, we might need to rethink how PPGS groups or clusters the meal composition. Rather than focusing on nutrient value, the current clustering techniques aim to describe the apparent characteristics of the food. The traditional approach and the balanced energy approach differ greatly because of this fact. Additionally, attempting to reduce the nutrient conformance standard deviation is hampered by this fact. The group's general nutrient composition, including protein, lipids, carbohydrates, and fibre, should be described in the ideal clustering.

traditional approach

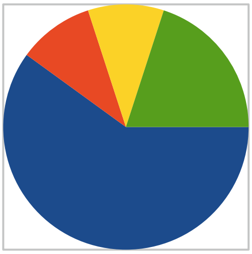


balanced energy approach



restricted balanced energy approach

balanced macronutrient approach



balanced nutrient approach

Staple Foods = blue

Side Dishes = red

Vegetables = yellow

Fruits = green

legends

Fig. 1. Food ratio of each approach

The outcome of the algorithm we have to describe in equation (1) surprises us. We've demonstrated it as a macronutrient and nutrient-balanced approach. The outcome appears to be more imbalanced than the conventional approach. In addition, the nutritional value is more balanced than with the same method. We have shown this reality as a lower standard deviation of supplement conformance.

We are aware of the research's flaws. First, we didn't take into account factors like culture, location, and concerns about national policies. We have accepted the TKPI as is, even though some of the contents, such as crocodile meat, are exotic. Second, we assumed the accuracy of the TKPI. Some of it hasn't been updated since 1960 [28], which could raise accuracy concerns. Thirdly, the national daily recommended intake base value is the only one we employ. On the other hand, researchers can apply our techniques to other age and gender groups that are described in the same data. We planned to incorporate those into subsequent development. The creation of mobile-based tools for simple food ratio implementation would be part of the plan. In addition, we are thinking about running an experimental trial to see how this approach stacks up against more established ones in community settings.

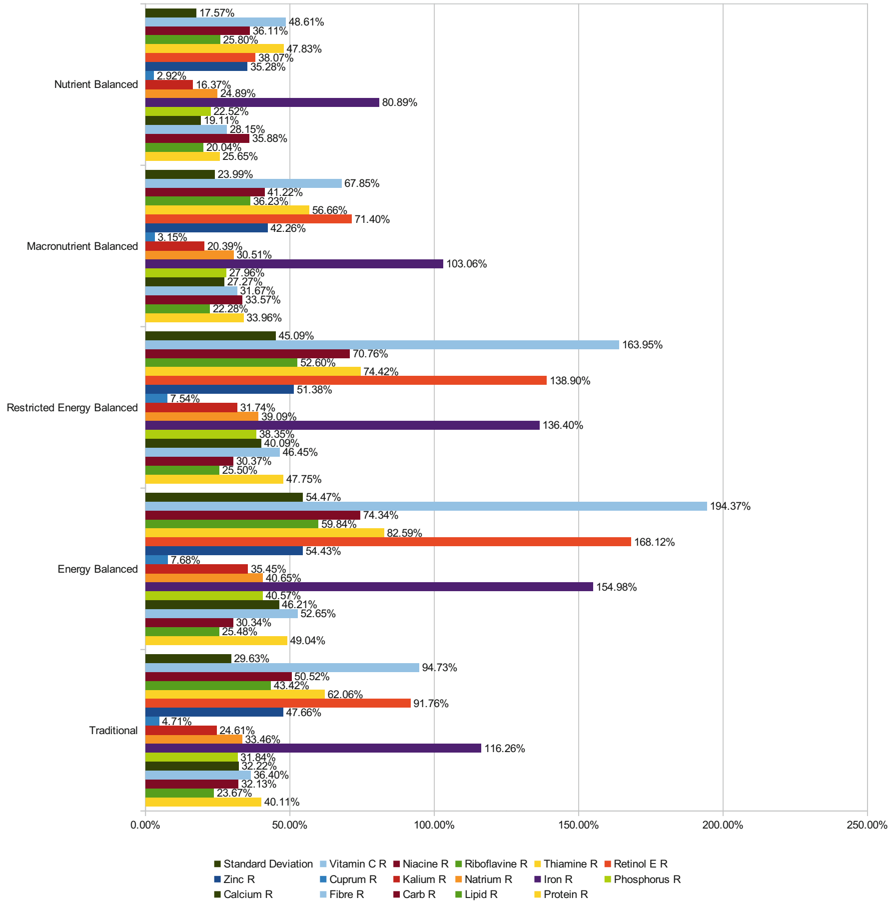


Fig. 2. Indonesian Daily Recommended Intake Conformance of each approach. We have taken the calculation from 600 kcal meals.

5 Conclusions

The artificial intelligence-based method can be used by researchers to determine the ideal meal composition ratio. Additionally, we have demonstrated that the food composition table's clustering modification may require some modification.

Acknowledgement. Kementrian Pendidikan dan Kebudayaan – Badan Riset Inovasi Nasional has supported this study with grant Penelitian Riset Pemula PDP-KemenristekBRIN 3a86ec40-0a25-4bfc-a74c-4241cadd5590.

We want to thank Konsorsium Penelitian Kadar Biomarker Darah Non-Invasive between IPB University, the Agency of Assessment and Application of Technology, and PT Tesena Inovindo for their continued support of our research.

We declare no competing interest.

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