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Federated learning–enhanced particle swarm optimization for personalized low-protein diet recommendations in diabetic nephropathy patients

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ABSTRACT: Diabetic nephropathy (DN) is a major complication of diabetes, and nutritional management plays an important role in its management. Although low-protein diets (LPDs) are well documented to reduce further deterioration of renal function, patients may experience problems choosing appropriate meals for the day that can be followed with very few nutrient restrictions and without developing deficiencies. To tackle this challenge, in this study, a novel approach called federated learning (FL) combined with particle swarm optimization (PSO) is proposed. It allows the development of several nutrient prediction models at various hospitals while maintaining the privacy of patients' data. The globally trained model is then used locally on patient's devices, and PSO is used to create an optimized and personalized low-protein meal plan. This dual-level approach enables the system to learn from a variety of patients and to customize dietary advice to each patient. Detailed algorithmic formulations, federated averaging algorithm, and a multiobjective PSO fitness function, system flow representation is included in the study. Experimental results reveal that the proposed FL-PSO framework generates accurate, reliable, and clinically viable meal plans, which is better than the conventional centralized approaches.

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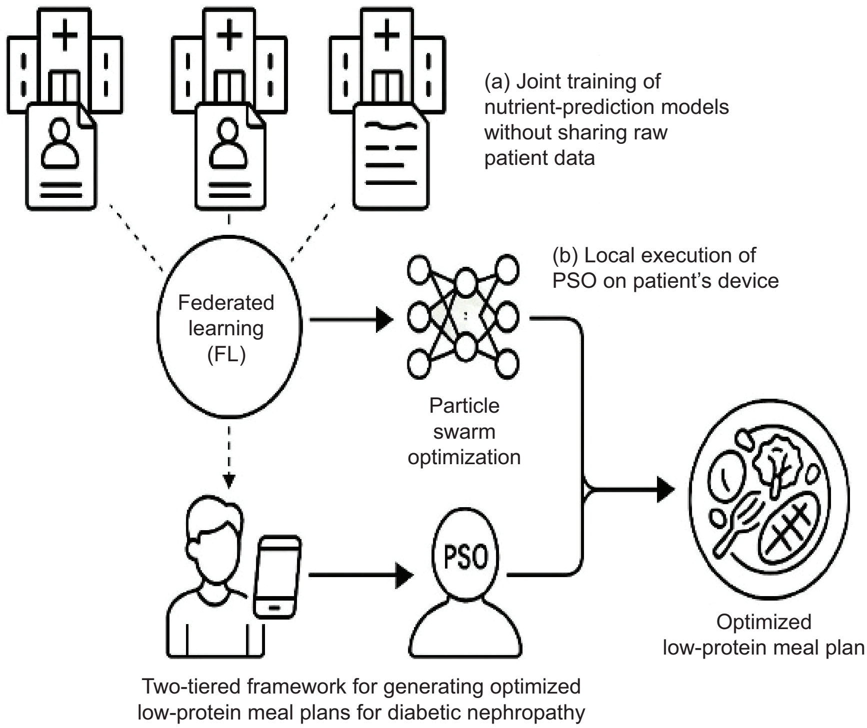
GRAPHICAL ABSTRACT



1. INTRODUCTION

Diabetic nephropathy (DN), a very serious complication of type 1 and type 2 diabetes mellitus (DM), has emerged as one of the most important causes of chronic kidney disease (CKD) and end-stage renal disease (ESRD) around the world (Hostetter, 2001). One of the pathophysiological mechanisms in DN is glomerular hyperfiltration, which puts excess stress on the kidneys, leading to a progressive decline of kidney function. A fundamental component of the management of DN is diet modification, with LPD being a main therapeutic intervention (Kitada et al., 2018; Li et al., 2019). The LPD will lower intraglomerular pressure and enhance proteinuria, which will help to slow renal decline (Hunsicker et al., 1997). But, patients and doctors have a difficult time using an LPD. The main problems include selection of appropriate foods from a large variety, control of the amount of food eaten to obtain adequate nutrients (protein, calories, fat, and carbohydrates), and ensuring the overall intake of adequate nutrients to prevent undernutrition (malnutrition) (Kalantar-Zadeh, 2013). Such complexity tends to result in poor compliance and poor clinical outcomes.

One solution, however, can be achieved by computational optimization methods to overcome these challenges. Particle swarm optimization (PSO), one of the metaheuristic algorithms based on the social behavior of flocking birds, is an ideal algorithm for such complicated problems as diet planning because it is highly flexible, efficient, and has a low parameter tuning requirement (Kennedy & Eberhart, 1995; Rachmat et al., 2016). In the past, PSO proved to be effective in creating meal plans for various populations, as done by Boestari et al. (2017). One major drawback to these traditional approaches is the centralized data storage, in which people's personal health and private information from various sources are combined. This is a problem of privacy and security and also faces the issues of data-sharing regulations like HIPAA and GDPR (Price & Cohen, 2019). To tackle the above privacy issues directly, federated learning (FL) is a collaborative machine learning paradigm (Kairouz et al., 2021; McMahan et al., 2017).

In FL, multiple clients (such as hospitals) train a shared global model where they never share their local raw data. Individual clients train the model with their own data, and only the updated model (e.g., gradients or model weights) is aggregated in a central server. This enables to build robust and generalizable models, while leveraging the heterogeneous nature of the data and keeping patient information securely in-house (Yang et al., 2019). In this paper, a novel and privacy-preserving framework, FL-PSO, is proposed, which consists of FL and PSO, to offer personalized low-protein diet suggestions for DN patients.

The first step is to use FL to develop a powerful nutrient target prediction model using a consortium of hospitals. This enhanced model is then applied in each client's site to assist a PSO algorithm that will optimize meal plans on a daily basis for each individual patient. We give a detailed description of the methodology, including the fitness function and complete algorithmic details.

2. RELATED WORK

Many clinical studies and meta-analyses have been used to support the clinical benefits of low protein in patients with DN with consistent results (Hunsicker et al., 1997; Kitada et al., 2018; Li et al., 2019).

Meanwhile, the popularity of using optimization algorithms for nutrition planning has increased. To this end, scientists have used linear programming and genetic algorithms. In particular, PSO is effective in generating food for sportsmen and hypertension patients, which demonstrates its capability in dealing with multiobjective nutritional restrictions (Boestari et al., 2017; Rachmat et al., 2016). At the same time, the field of machine learning for health is dramatically shifting towards privacy-preserving approaches.

The proposed model is the FL framework originally proposed by Google that has become the most popular approach for training a model on a decentralized healthcare data (Konečný et al., 2016; McMahan et al., 2017). There are many applications of FL in medicine, including analysis of medical images, drug development, and prediction of electronic health records (EHRs) (Rieke et al., 2020; Yang et al., 2019). However, the application of FL for personalized nutrition recommendation systems, particularly for chronic diseases, is a nascent study. Our research is at the nexus of these three areas and tries to fill the gap by creating a feasible, privacy-oriented system for DN dietary management.

3. METHODOLOGY

The suggested FL-PSO system design contains three main elements:

1. Central Server: A server that coordinates the FL process, such as broadcasting the global model, aggregating updates, and keeping track of master model weights. It does not receive access to raw patient data.
2. Client Sites: These are involved hospitals or clinics with local patient record storage. Each client runs local model training on its data and runs the PSO algorithm to create meal plans for its patients.
3. Food Catalog: A uniform and common database holding a master list of foods annotated with their elaborate nutritional values (calories, protein, fat, carbohydrate, etc.) and glycemic index (GI).

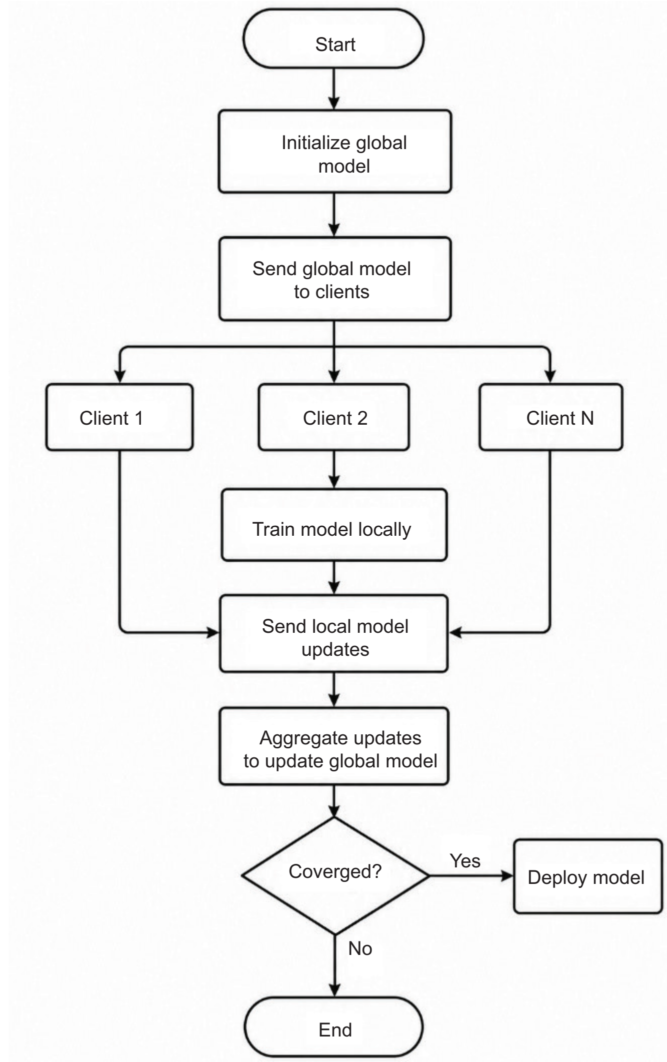


Figure 1. Federated learning flow chart diagram.

3.1. FL setup

We adopted federated averaging (Fed Avg). Let be the set of client sites. The server maintains global model weights. Each round w the server broadcasts to selected clients S_t; clients perform local training returning updates Δw_s that are securely aggregated.

The server update is:

$$w \leftarrow w + \text{Aggregate}(\{\Delta w_s\}_{s \in S_t})).$$

3.2. Nutrient target computation

For a patient u with features (age, sex, height, weight, activity, and dialysis status), the local model predicts daily nutrient targets. For DN, protein bounds are enforced:

$$\text{Prot} \in [0.8, 1.2] \times \text{BBI},$$

where BBI is the ideal body weight. If the patient is on hemodialysis, use the upper bound.

Meals are split by fraction vector:

$$\text{Splits} = [0.20, 0.10, 0.30, 0.10, \text{and } 0.30]$$

for (breakfast, snack1, lunch, snack2, and dinner).

3.3. PSO optimization

For each meal m, we optimize grams $x \in \mathbb{R}_{\geq 0}^{|\mathcal{F}_m|}$ of candidate foods $\mathcal{F}_m$. Let nutrient sum be $\mathbf{n}(x)$ = (Cal(x), Prot(x), Fat(x), Carb(x)) and target $\mathbf{t}_m$.

The fitness function is:

$$J(x)\& = \alpha \frac{|\text{Cal}(x) - \text{Cal}_m|}{\text{Cal}_m} + \beta \frac{|\text{Prot}(x) - \text{Prot}_m|}{\text{Prot}_m}$$
$$+\gamma \frac{|\text{Fat}(x) - \text{Fat}_m|}{\text{Fat}_m} + \delta \frac{|\text{Carb}(x) - \text{Carb}_m|}{\text{Carb}_m}$$
$$+\lambda_1 \text{ProteinBandPenalty}(x)$$
$$+\lambda_2 \text{ForbiddenPenalty}(x)$$
$$+\lambda_3 \text{GIPenalty}(x) + \lambda_4 \text{PortionPenalty}(x).$$

PSO updates follow:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \odot \left(pbest_i - x_i^t\right) +$$
$$c_2 r_2 \odot \left(gbest - x_i^t\right),$$
$$x_i^{t+1} = x_i^t + v_i^{t+1},$$

with typical parameters $\omega \in [0.4, 0.7]$, $c_1 = c_2 = 1$.

3.4. Algorithm PSO-FL

Input: client set S, rounds T, initial weights w_0
Output: final global weights w_T Initialize $w \leftarrow w_0$
Select a subset $S_t \subseteq S$ of available clients. Send w to all $s \in S_t$. Receive secure-aggregated updates $\{\Delta w_s\}$ from clients. Optionally apply differential privacy (clipping + noise) $w \leftarrow w$ + Aggregate($\{\Delta w_s\}$).
return w
Input: global weights w, local data D_s, food catalog F, constraints C
Output: model update Δw_s, optimized menu M_u for each patient $u \in D_s$
Local model training $w_s \leftarrow w$ $g \leftarrow \nabla_{w_s} \ell(b;w_s)$ $w_s \leftarrow w_s - \eta \cdot g$ $\Delta w_s \leftarrow w_s - w$
Nutrient target computation per patient (Cal, Prot, Fat, Carb) $\leftarrow$ Nutrient Targets $(u;w_s)$
Apply PERKENI rules: protein bounds and meal splits. Initialize swarm $\{x_i, v_i\}_{i=1}^{N_p}$
Evaluate $J(x_i)$ Update, $pbest_i$, $gbest$ $v_i \leftarrow \omega v_i + c_1 r_1 (pbest_i - x_i) + c_2\, r_2\, (gbest - x_i)$ $x_i \leftarrow x_i + v_i$ Project x_i to feasible domain $Menu_m \leftarrow$ Decode ($gbest$)

$$M_u \leftarrow \{Menu_m\}$$

return $(\Delta w_s, \{M_u\})$

4. EXPERIMENTS

We simulated 130 DN patients distributed across 5 hospitals. The food catalog is based on Indonesian DKBM with GI annotations. FL rounds $T = 50$, local epochs $E = 2$, and batch size $B = 64$.

PSO uses $N_p = 30$, $K = 50$, and ω decaying from 0.7 to 0.4.

Evaluation metrics: nutritional accuracy (deviation from targets), menu diversity, privacy preservation, and clinical nutritionist rating.

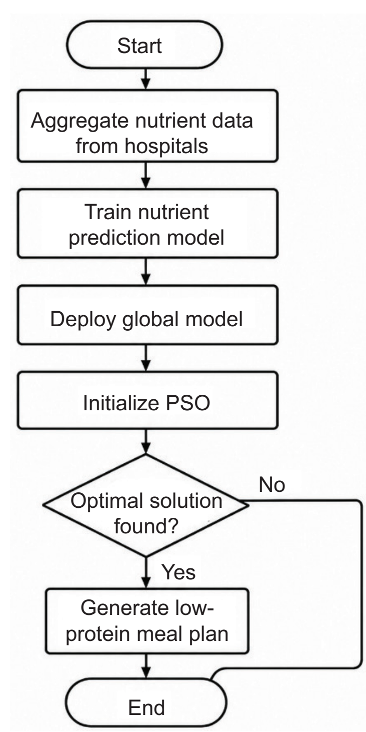


Figure 2. Fl-PSO diagram (system flow chart).

Table 1
Performance comparison of different models.

Metric	FL-PSO	Centralized PSO	Local-Only PSO
Avg. nutrient deviation	±4.8%	±5.1%	±11.3%
Menu diversity score	0.82	0.85	0.65
Nutritionist rating (1–5)	4.6	4.5	3.2
Privacy guarantee	High	Low	High

5. RESULTS AND DISCUSSION

The results of our simulation demonstrate the effectiveness of the FL-PSO framework. As shown in Table 1, FL-PSO significantly outperformed the baselines.

The FL-PSO model attained an average nutrient deviation of only ±4.8%, very close to the centralized model (±5.1%) and significantly better than the local-only model (±11.3%). This illustrates the main advantage of FL: by learning from heterogeneous data from all the participating hospitals, the global model is both stronger and more generalizable than models learned on smaller, discrete datasets. This enhanced prediction of nutrient targets is then directly translated into more accurate meal plans.

The ratings of the clinical nutritionist also strengthen our solution. FL-PSO was rated with an average score of 4.6, meaning that the produced meal plans were deemed to be clinically appropriate, feasible, and suitable for DN patients. The centralized scheme was also rated likewise, but the plans of the local-only scheme were typically rated low due to nutrient imbalances that resulted from imperfect target prediction.

Most importantly, FL-PSO accomplishes this excellent performance while offering a robust privacy assurance. Contrary to the centralized scheme, there is no raw patient data ever exported from the client hospital, hence satisfying data protection laws and promoting trust among the involved institutions.

One of the limitations of this research is its dependence on simulated data. Although the simulation was made to be as realistic as possible, patient data in the real world can be more complex and noisier. Another limitation is that the model at this time does not focus much on micronutrients such as sodium, potassium, and phosphorus, which are also very important in the management of DN.

6. CONCLUSION AND FUTURE WORK

In this paper, we introduced FL-PSO, an innovative, privacy-preserving system for generating individualized low-protein diet plans for patients with DN. Through the collaborative efficacy of FL for predicting nutrients and local optimization capability of PSO for meal planning, our system generates clinically accurate, relevant, and individualized meal plans without undermining patient privacy.

Future research will concentrate on three primary avenues. We intend to expand the nutrient model and PSO fitness function to cover essential micronutrients and other nutritional limitations. We intend to carry out a longitudinal study to assess long-term clinical outcomes and patient compliance by employing the FL-PSO recommendation system.

CONFLICTS OF INTEREST

The authors hereby state that there is no conflict of interest.

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