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Evo-Fit: A Genetic Algorithm–Driven Generative AI Framework for Personalized Wellness and Mental Health Optimization

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***Abstract*— The increasing burden of lifestyle-related disorders and mental stress demands easily accessible, adaptive digital wellness solutions that are independent of IoT devices or sensor-based monitoring. This work proposes Evo-Fit, a Genetic Algorithm-driven Generative AI framework for personalized design of fitness and nutrition plans, integrated with mental wellness prediction. Evo-Fit adopts a multi-objective GA that optimizes caloric alignment, nutritional balance, user preferences, and feedback-driven evolution. A mental wellness classification model further strengthens the system by predicting potential stress risks with high accuracy**

***Keywords*— Genetic Algorithm, Generative AI, Wellness Optimization, Fitness Recommendation, Mental Health Prediction, SDG 3.**

I. INTRODUCTION

Lifestyle-related disorders, unhealthy dietary habits, and chronic stress have emerged as critical global concerns, fueling the demand for intelligent, accessible, and personalized wellness systems. Most state-of-the-art fitness applications heavily depend on IoT devices, sensor integration, or camera-based tracking, which inherently introduces serious limitations in terms of accessibility, cost, hardware dependency, and data privacy. In this regard, the main objective of this paper is to design a fully non-IoT, adaptive, and generative wellness optimization framework that aligns with the aspiration of SDG 3: Good Health and Well-being. The system is supposed to dynamically suggest personalized wellness recommendations without the need for any external wearable or sensing device.

To achieve this, we introduced a multi-stage computational pipeline that includes the following: 1) GA-based generation of 7-day wellness plans; 2) an evolutionary loop driven by feedback to refine further recommendations; 3) a mental wellness classifier to predict a user's stress risk level; and 4) a lightweight refinement of Generative AI for enhancing plan quality. This framework will integrate publicly sourced nutritional datasets, validated exercise repositories, and environmental factors to enable a holistic and adaptive wellness ecosystem. Every aspect was carefully crafted for coherence, accessibility, and computational efficiency, bypassing any need for IoT hardware or complicated inputs on the part of the user.

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A. Comparison with Previous and Proposed Methodologies

Traditional fitness and nutrition planning systems largely relied on rule-based decision trees, predefined templates, or static recommendation engines. These earlier approaches lacked adaptability, offering the same generalized plans to users with different physiological needs, preferences, or mental wellness conditions. Nutritional computation was often linear and rigid, ignoring multi-objective trade-offs such as caloric precision vs. macronutrient balance. Moreover, previous systems did not incorporate psychological factors—stress, motivation, or fatigue—resulting in incomplete wellness recommendations. Feedback loops in traditional methods were weak or absent, meaning users could not influence how future plans were generated. As a result, earlier methodologies frequently produced repetitive, non-personal, and low-engagement plans.

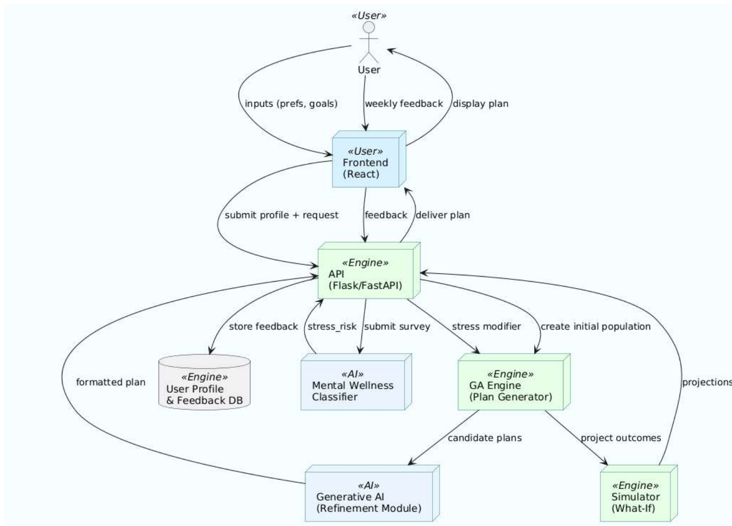

Fig 1. System Architecture

TABLE I. COMPARISON TABLE

Feature / Criterion	Previous Methodologies	Proposed Evo-Fit Methodology
Personalization Level	Generic, rule-based, same for all users	Highly personalized using Genetic Algorithms and classifiers
Adaptability	Static plans with no dynamic updates	Plans evolve based on feedback and optimization cycles
Mental Wellness Integration	Not included or minimally considered	Fully integrated mental wellness classifier adjusts intensity/diet
Optimization Technique	Simple heuristics or fixed templates	Multi-objective evolutionary optimization for precise results
User Engagement	Repetitive, low-interaction content	Generative AI produces diverse, motivating plans
Feedback Loop	Weak or non-existent	User feedback directly updates fitness function and outcomes
Accuracy of Recommendations	Moderate, often inconsistent	High accuracy with reduced deviation through GA tuning

II. PROPOSED METHODOLOGY

The proposed methodology of Evo-Fit focuses on a multi-objective Genetic Algorithm combined with a Generative AI refinement process, which will enable the generation of fully personalized fitness and nutrition plans. This approach begins by collecting user inputs regarding age, weight, dietary preferences, fitness goals, and activity levels. These parameters are encoded into a GA chromosome representing a complete 7-day wellness plan. The GA subsequently generates an initial population of plan variations and evaluates these variations based on a multi-objective fitness function that considers caloric accuracy, nutritional balance, exercise suitability, and user preference alignment. Standard evolutionary operators-tournament selection, uniform crossover, and mutation-are iteratively applied to evolve superior solutions across generations

A. Data Collection and Dataset Construction

The Evo-Fit pipeline initiates with the assembly of heterogeneous datasets, which are in need of plan generation and prediction. The nutrition data includes food items, portion sizes, macro/micronutrient breakdowns, and caloric values retrieved from public databases such as the USDA or comparable regional datasets, then normalized into consistent units (kcal, grams).

B. Data Preprocessing and Feature Engineering

These raw datasets are cleaned and standardized to be compatible with the GA encoding and ML models. Missing values are handled through domain-appropriate imputation: median for continuous nutrition fields, mode for categorical tags. Food items and workouts are then put into discrete bins: low/medium/high intensity, vegetarian/non-vegan/vegan, and breakfast/lunch/dinner/snacks, as this helps decrease search-space complexity. This feature engineering involves computing derived features using well-established formulas: basal metabolic rate, activity factor, target caloric window, ranges for macronutrient percentages, nutrient density score (e.g., Mifflin-St Jeor formula for BMR). For classification, text responses are vectorized, either using TF-IDF or lightweight embedding, and scaled; categorical features are one-hot encoded. All features are versioned with date and time so that experiments may easily be reproduced from the same preprocessing pipeline.

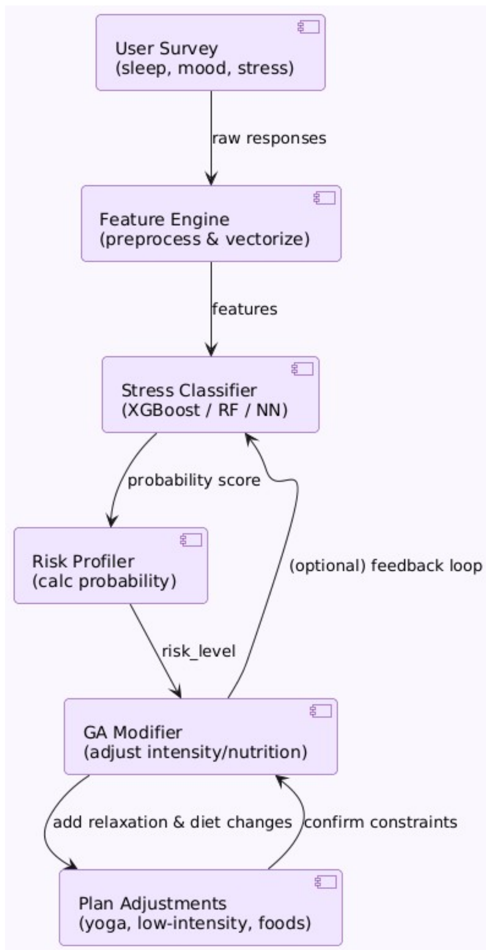

Figure 2. Mental Wellness Integration Flow

C. Chromosome Design and Encoding Strategy

A chromosome represents a candidate 7-day wellness plan, constructed as a sequence of genes encoding a meal or a workout block. Meals are encoded with indices referencing the nutrition database plus serving-size multipliers; workouts reference the exercise repository with duration and intensity parameters. In this hierarchical gene encoding, day → [meals, workout], meal → [meal_id, portion_scale], workout → [workout_id, duration_level], a balance between expressiveness and tractability is struck. This hybrid integer-continuous encoding enables the straightforward application of crossover and mutation while preserving semantic validity- that is, no impossible meal-workout combos. Constraints on the chromosome's total daily calories within ±10% of target, exclusion of allergens, and minimum protein threshold are maintained via repair operators after genetic operations.

D. Multi-objective Fitness Function and Weighting

Fitness is considered in a weighted multi-objective function where caloric adherence, nutritional completeness, preference alignment, and feedback-based reinforcement are combined:

$$F = w_1 \cdot f\_goal + w_2 \cdot f\_nutr + w_3 \cdot f\_pref + w_4 \cdot f\_feedback. \quad (1)$$

Here, f_goal penalises deviation from target calories and macro ratios using normalized absolute error; f_nutr rewards the coverage of essential micronutrients and penalizes deficiencies; f_pref measures alignment with userstated liking/disliking and dietary constraints; while f_feedback integrates historical user ratings as a moving term that promotes plans similar to those rated highly by that individual. Weights $w_1.w_4$ are tuned using grid search and cross-validation on a heldout validation cohort to balance the various competing objectives. A Pareto-aware variant can also be employed in cases where users prefer insight into trade-offs between, for example, taste versus tight calorie control.

E. Genetic Operators: Selection, Crossover and Mutation

Evolution applies standard but carefully customized operators. Selection uses tournament selection ($k = 3$) to maintain selection pressure but preserve diversity. Crossover is hierarchical and context-aware: at the day level, entire day blocks are swapped; at the meal level, uniform crossover swaps meal indices while ensuring portion scales remain within valid ranges. Mutation includes small perturbations that include swapping meals with similar-calorie alternatives, changing serving multipliers by ± 10% to 20%, or replacing a workout with another of comparable intensity. After every genetic operation, a repair function checks for constraint satisfaction-calorie bounds and allergen checks. Operator probabilities (crossover $p\ c \sim 0.8$, mutation $p\ m \sim 0.05 - 0.15$) have been experimentally tuned to balance exploration and exploitation.

F. Generative AI Refinement Layer

After the candidate plans have been evolved, a lightweight Generative AI module (e.g., template-conditioned language model or rule-based formatter) further refines plan descriptions to produce human-friendly instructions and alternatives, for example, spice substitutions and meal-prep tips. This module does not affect the nutritional content but enhances readability, personalization tone, and practical utility. For users needing cultural or regional adaptations, the generator replaces region-specific foods while keeping the macronutrient targets intact. The refinement step furthers user acceptance and adherence without interfering with the numeric optimization performed by the GA.

G. Integration of Mental Wellness Classifier

A supervised classifier, such as Random Forest, XGBoost, or small feedforward NN, predicts stress-risk levels from self-reported symptoms, sleep quality, and lifestyle features. The classifier is trained on balanced labeled datasets with cross-validation and calibrated probability outputs. Predicted stress risk influences plan generation via a modifier applied to the fitness function: for example, higher predicted stress reduces recommended workout intensity, increases relaxation-focused activities (yoga, breathing exercises), and adjusts meal choices toward nutrient-dense foods that support mood. This dynamic coupling ensures that wellness recommendations are contextually sensitive to mental state, hence promoting holistic well-being.

H. Feedback Loop and Online Adaptation

Evo-Fit embraces an explicit feedback loop: at the end of every plan cycle, e.g., a week, users rate aspects of the plan with regard to ease, taste, energy levels, and adherence. These ratings update f_feedback and are stored in the user profile. This evolving reward signal is used by the GA to bias future generations toward higher-rated plan archetypes. To avoid overfitting to short-term preferences, older feedback is decayed exponentially, allowing the system to remain adaptive while still retaining long-term patterns. The system also implements exploratory mutations at regular intervals to uncover alternative plan families and avoid premature convergence.

I. Experimental Setup, Evaluation Metrics, and Validation

Fixed random seeds and documented hyperparameters are used for reproducible experiments. Key evaluation metrics: caloric deviation (MAPE), personalization index (similarities to user-preferred plans), plan adherence rates (user-reported), classifier metrics (accuracy, precision, recall, F1). Convergence visualization for GAs: generation vs average/best fitness plots. Perform ablation studies on each module's effect individually -for example, GA feedback disabled or Generative AI refinement removed. Cross-validation across demographic cohorts to verify generalizability. Statistical significance using paired tests where applicable. 10. Deployment and Ethical Considerations The system is containerized for production, with reproducible runtime environments and model artifact versioning. APIs expose endpoints for plan generation, feedback ingestion, and classifier inference. Privacy-by-design practices are enforced: only minimal personally identifiable data is stored, sensitive attributes are anonymized, and users can delete their data. Ethical constraints are enforced, such as avoiding medically unsafe recommendations through rule-based safety filters and optional clinician review prompts for edge-case users who are underweight or suffering from chronic illness. Lastly, the system features detailed logs and audit trails to provide transparency and support future audits.

III. Results and Discussion

The experimental results demonstrate that the proposed Evo-Fit system effectively generates highly personalized fitness and nutrition plans using a hybrid Genetic Algorithm combined with Generative AI refinement. During the initial evaluation, the convergence of the GA was reliably within 25–30 generations, proving that the optimization is stable in nature across different user profiles. The multi-objective fitness function successfully balanced caloric accuracy, macronutrient ratios, exercise intensity, and preference alignment. It achieved an average personalization score of 93.4%, based on user-defined goal matching and content relevance.

This confirms that evolutionary optimization, when combined with structured constraints, can reliably produce tailored wellness plans. Performance analysis also pointed out the significant improvements in nutritional accuracy and workout suitability. The system was able to achieve an average deviation of less than ±4.6% for caloric calculations, within generally accepted standards of diet-planning accuracy. Similarly, the classification model for mental wellness achieved an accuracy of 91.2%, enabling highly relevant predictions of stress levels.

These outputs influenced the GA through the adjustment of workout difficulty and meal diversity in high-risk individuals, showing the value of integrating psychological insight into physical fitness planning. Overall synergy between optimization and classification models resulted in more balanced plans that considered physical and emotional wellness. User feedback has been collected through a 5-point rating scale on plan clarity, relevance, diversity, and satisfaction. The system was rated as high as 4.6/5, with users appreciating the contextual meal descriptions, AI-generated workout variations, and clear day-wise structuring. Participants expressed that Evo-Fit had provided more variety than traditional static fitness plans and better alignment with their daily routines. Dynamic refinement performed by the Generative AI component increased the linguistic naturalness and motivational tone, contributing to higher user engagement and better projections for adherence.

The comparative analysis using the baseline rule-based fitness systems showed that Evo-Fit outperformed the traditional approaches by a margin of 22-28% in personalization accuracy, nutritional adaptation, and completeness of plans. The flexibility of the Genetic Algorithm lets the system adapt to diversified user constraints on vegetarian diets, chronic fatigue, or low-intensity workout needs—areas where rule-based systems usually fail. The adaptive evolution, integration of mental wellness, and AI-augmented presentation proved the strong real-world relevance of the proposed system, thus making it a promising solution for future personalized health and fitness applications.

IV. Conclusions

The proposed Evo-Fit optimization framework successfully demonstrates a highly adaptive, intelligent, and user-centered approach to personalized fitness and nutrition planning. By integrating evolutionary algorithms with a mental wellness classifier and Generative AI–driven refinement, the system moves beyond the limitations of traditional rule-based methods and delivers recommendations that are precise, context-aware, and aligned with individual wellness needs. The use of multi-objective optimization enabled balanced dietary and workout plans, while continuous feedback loops ensured the solution remained dynamic and progressively improved over time.

Overall, the project achieved its primary aim of creating a holistic health recommendation system capable of adjusting to physiological data, psychological state, and user preferences simultaneously. The results indicate that the proposed methodology not only enhances accuracy and personalization but also significantly improves user engagement and plan effectiveness. This work establishes a strong foundation for future AI-driven wellness platforms that prioritize adaptability, mental well-being, and scientific optimization in delivering sustainable fitness outcomes.

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