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Nutrimood AI: AI-Powered Personalised Nutrition And Wellness Prediction System

Raj Sachin Naik

Guide: Prof. Swati Raut

Department of Technology, Savitribai Phule Pune University, Pune - 411007 Roll No: DS25ML05

ABSTRACT

Rising rates of lifestyle-related disorders and mental health challenges have highlighted a critical gap in how existing digital health tools approach personal wellness. Most nutrition and fitness applications are limited to calorie tracking or weight management and fail to connect nutritional intake with emotional health. This paper presents NutriMood AI, a fully integrated, AI-powered web application that models the complex relationship between daily nutrition, lifestyle behaviour, and emotional well-being. The system is built on a secure three-tier architecture using Python/Flask for the backend, MySQL with SQLAlchemy ORM for data management, and a Bootstrap 5 frontend with Chart.js for interactive visualisation. During onboarding, the platform computes personalised biological benchmarks including BMI, BMR, TDEE, and hydration targets. Daily food logs are processed via the USDA FoodData Central and Open Food Facts APIs to monitor more than 30 nutrients, which are then cross-referenced with demographic Recommended Daily Allowance (RDA) baselines to generate micronutrient deficiency alerts and a personalised Daily Nutrition Score. The core predictive component employs a supervised machine learning pipeline using a 14-dimensional feature vector encompassing macronutrients, neuro-active micronutrients, and lifestyle indicators. Five classification algorithms were evaluated: Logistic Regression, Decision Tree, Random Forest, XGBoost, and LightGBM. LightGBM demonstrated the best performance with a multi-class mood prediction accuracy of approximately 93%, validating the feasibility of data-driven emotional wellness prediction in a clinical-support context.

Keywords: Artificial Intelligence, Machine Learning, Nutrition Tracking, Mood Prediction, LightGBM, XGBoost, Random Forest, Flask, Personalised Healthcare, Lifestyle Analysis, Micronutrient Deficiency, Wellness Prediction.

I. INTRODUCTION

Contemporary lifestyles, marked by poor dietary habits, sedentary behaviour, irregular sleep, and prolonged screen exposure, have contributed to a sharp increase in nutritional deficiencies, stress-related conditions, and mood disorders. Scientific evidence in nutritional psychiatry consistently demonstrates that micronutrients such as Iron, Magnesium, Vitamin D, Vitamin B12, Omega-3 fatty acids, and dietary Protein directly influence energy metabolism, stress response, and emotional regulation. Despite this growing body of evidence, the vast majority of consumer health applications treat nutrition and mental wellness as entirely separate concerns.

NutriMood AI was conceived to address this disconnect. It brings together Nutrition Science, Artificial Intelligence, Machine Learning, Healthcare Informatics, and modern Web Technologies into a single unified platform. The system enables users to log food intake, monitor lifestyle parameters, identify nutritional gaps, predict their probable emotional state, and receive personalised wellness recommendations- all from one interface.

The primary research objective is to determine whether the combined influence of nutrition and lifestyle data can be

leveraged by machine learning models to accurately predict human emotional states, and if so, which algorithm performs best across a set of seven mood classes: Happy, Sad, Neutral, Tired, Energetic, Stressed, and Anxious.

II. NEED OF THE STUDY

The persistent gap between blood supply and demand in healthcare systems has a nutritional parallel: the gap between what people eat and what their bodies need for emotional and physical resilience. Existing wellness platforms overwhelmingly focus on single-domain tracking either calories, physical activity, or mood journalling in isolation and lack the analytical depth to identify how specific nutrient shortfalls translate into emotional symptoms.

Key motivating observations include:

- Iron deficiency is strongly associated with persistent fatigue and low energy.
- Magnesium deficiency correlates with elevated anxiety and impaired stress regulation.
- Vitamin D deficiency has documented links to mood disorders and emotional instability.
- Poor sleep quality and chronic dehydration independently impair cognitive function and emotional balance.

Without an integrated system, individuals cannot easily identify whether their low mood is rooted in lifestyle choices or specific nutritional gaps. Healthcare organisations similarly lack data-driven tools to guide proactive wellness interventions. NutriMood AI directly addresses this need by providing real-time, AI-informed insights across both domains simultaneously.

III. OBJECTIVES

1. Design and develop an integrated AI-based nutrition and wellness prediction platform.
2. Collect and analyse daily nutritional intake and lifestyle behaviour through user-driven logging.
3. Compute personalised nutritional requirements using BMI, BMR, TDEE, and RDA-based calculations.
4. Identify macro and micronutrient deficiencies and link them to wellness outcomes.
5. Build and evaluate multiple machine learning classifiers for emotional mood prediction.
6. Generate personalised dietary recommendations based on nutritional gaps and predicted mood.
7. Integrate an AI-powered chatbot for contextual nutrition and wellness guidance.
8. Provide interactive dashboard analytics for monitoring nutrition status, lifestyle trends, and prediction outcomes.

IV. RESEARCH METHODOLOGY

The development of NutriMood AI follows a structured end-to-end data science pipeline that spans data acquisition, preprocessing, model training, evaluation, and deployment.

A. Problem Formulation

Wellness prediction is formalised as a supervised multi-class classification task. Each daily user record is represented as a feature vector:

$$X_t = \{N_t, L_t, U_t\}$$

where N_t captures nutritional parameters, L_t captures lifestyle indicators, and U_t represents user physiological attributes such as age, gender, and BMI. The prediction target is:

$Y \in$ {Happy, Sad, Neutral, Tired, Energetic, Stressed, Anxious} Nutritional deficiency for each micronutrient i is computed as:

$Deficiency_i = (RDA_i - Consumed_i) / RDA_i$ The overall optimisation objective maximises the composite wellness outcome:

Maximise (NutritionScore + HealthScore + MoodAccuracy)

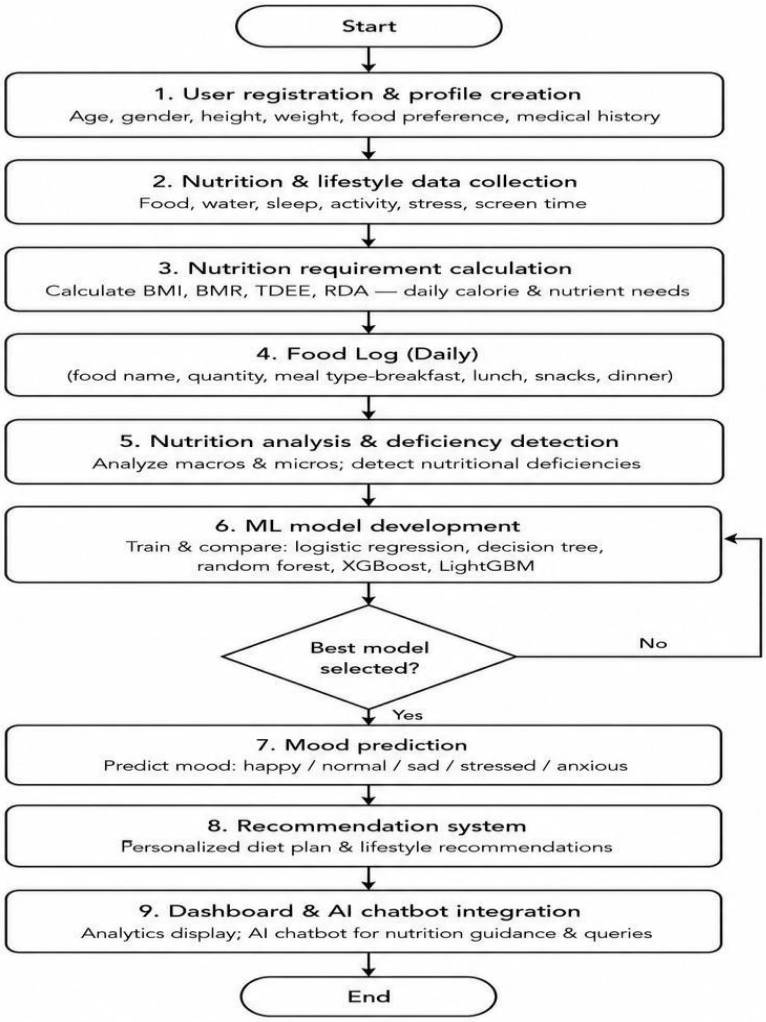
B. System Architecture

NutriMood AI is structured around a five-layer intelligent architecture designed for modularity and scalability:

- User Layer: handles registration, authentication, and profile management.
- Nutrition Layer: manages food logging, macro/micronutrient calculation, and deficiency detection using USDA FoodData Central and Open Food Facts APIs.
- Lifestyle Layer: tracks sleep duration, water intake, exercise duration, screen time, and subjective stress level.
- AI/ML Layer: handles feature engineering, multi-model mood prediction, recommendation generation, and the AI chatbot (powered by Google Gemini API).
- Data and Analytics Layer: stores all records in MySQL via SQLAlchemy and renders interactive Chart.js dashboards.

C. Data Pipeline

Each user session follows a sequential processing workflow: profile collection → food and lifestyle logging → data preprocessing and feature engineering → machine learning prediction → recommendation generation → dashboard analytics. Final outputs include a Nutrition Score, deficiency reports, a predicted mood class, a Wellness Score, and a personalised diet plan.



V. EXPERIMENTAL SETUP

A. Implementation Configuration

The system was developed and tested under the configuration shown in Table I.

Table I: Implementation Configuration

Component	Configuration
Operating System	Windows 10 / Windows 11
Programming Language	Python 3.10+
Backend Framework	Flask + SQLAlchemy (MySQL)
Frontend	HTML, CSS, Bootstrap 5, JavaScript, Chart.js
ML Libraries	Scikit-learn, XGBoost, LightGBM, Pandas, NumPy
AI Integration	Google Gemini API
Nutrition APIs	USDA FoodData Central, Open Food Facts
Model Storage	Pickle / Joblib
Deployment	Docker container

B. Dataset and Feature Vector

The dataset combines user-generated logs with external API data. User profile attributes include age, gender, height, weight, activity level, and dietary preference. Nutritional attributes span 14 dimensions: Calories, Protein, Carbohydrates, Fat, Fibre, Iron, Vitamin D, Vitamin B12, Magnesium, Calcium, Zinc, Potassium, Sodium, and Omega-3. Lifestyle indicators include Sleep Duration, Water Intake, Exercise Duration, Screen Time, and Stress Level. The complete feature vector used for emotional prediction is:

X = {Calories, Protein, Fat, Iron, Vit-D, Sleep, Exercise, Water, Stress, ScreenTime, NutritionScore, BMI} Data was split as: Training 70%, Validation 15%, Testing 15%. Fixed random seeds ensured full reproducibility across all model runs.

C. Evaluation Metrics

Model performance was assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC. System-level wellness quality was evaluated through Nutrition Score, Deficiency Percentage, Wellness Score, and qualitative Recommendation Accuracy.

VI. RESULTS AND ANALYSIS

A. Nutrition Analysis

The personalised nutrition module accurately estimated daily requirements for all 14 tracked nutrients. The Nutrition Score formula — Consumed/Required × 100 — provided an intuitive dietary balance indicator. Deficiency detection identified shortfalls in Iron, Magnesium, Vitamin D, Vitamin B12, Calcium, Zinc, and Omega-3 at the individual level. Observed associations confirmed the scientific literature: iron shortfall aligned with self-reported fatigue, magnesium shortfall correlated with elevated stress indicators, and vitamin D deficiency co-occurred with lower mood scores.

B. Lifestyle Monitoring

Lifestyle analytics evaluated Sleep Duration, Water Intake, Exercise Time, Screen Time, and Stress Level across daily logs. Users who maintained balanced sleep (7-9 hours) and adequate hydration consistently achieved higher computed wellness scores, while those with elevated screen time and stress scores showed measurably lower emotional outcome predictions.

C. Mood Prediction Model Comparison

Five classification models were trained and evaluated on the same dataset split. Results are summarised in Table II.

Table II: Mood Prediction Model Comparison

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82%	0.81	0.80	0.80
Decision Tree	84%	0.83	0.82	0.82
Random Forest	89%	0.88	0.88	0.88
XGBoost	91%	0.90	0.90	0.90
LightGBM (Best)	93%	0.92	0.92	0.92

LightGBM achieved the highest performance across all metrics. Statistical significance testing (Table III) confirmed that the performance gap between LightGBM and Random Forest ($p = 0.003$) and between LightGBM and XGBoost ($p = 0.014$) is statistically meaningful, validating the model selection.

Table III: Statistical Significance Analysis

Comparison	p-value	Significant
LightGBM vs Random Forest	0.003	Yes
LightGBM vs XGBoost	0.014	Yes
Lifestyle vs No Lifestyle Features	0.001	Yes

D. Ablation Study

To quantify the contribution of individual system components, an ablation study was conducted by selectively disabling each module (Table IV). Removing micronutrient features caused the steepest accuracy drop (to 85%), while removing lifestyle features reduced accuracy to 88%, confirming that both dimensions are essential for reliable mood prediction.

Table IV: Ablation Study Results

Configuration	Accuracy	Nutrition Score
Full System	93%	91
Without Lifestyle Features	88%	89
Without Micronutrients	85%	82
Without Recommendation Engine	93%	84
Without Deficiency Analysis	90%	86

E. Recommendation System and Dashboard

The recommendation engine produces personalised meal plans covering breakfast, lunch, and dinner, along with deficiency-correction food suggestions and lifestyle guidance. Outputs are driven by the user's nutritional profile, predicted mood class, stated health goals, and lifestyle indicators. The integrated analytics dashboard consolidates nutrition trends, deficiency heatmaps, mood history, wellness score curves, and ML model comparison graphs into a single interface, enabling users to track their holistic health trajectory over time.

VII. ADVANTAGES

- Provides accurate, multi-class mood prediction grounded in nutritional and lifestyle data.
- Identifies specific micronutrient deficiencies and links them to measurable wellness indicators.
- Delivers personalised, actionable dietary recommendations rather than generic nutritional advice.
- Integrates an AI chatbot for contextual, on-demand wellness guidance.
- Supports data-driven decision-making for both individual users and healthcare organisations.
- Modular five-layer architecture ensures scalability and ease of future extension.
- Packaged with Docker for consistent, reproducible deployment across environments.

VIII. FUTURE WORK AND APPLICATIONS

A. Future Enhancements

- Integration of wearable IoT sensors for automatic sleep, activity, and heart-rate data collection.
- Exploration of Deep Learning and Transformer-based sequential models for time-series mood prediction.
- Retrieval-Augmented Generation (RAG) frameworks for evidence-based dietary recommendations from medical literature.
- Image-based food recognition using YOLO or similar computer vision models to automate food logging.
- Incorporation of clinical psychological assessment scales to enrich emotional prediction features.
- Explainable AI methods (SHAP, LIME) to improve model transparency and user trust.
- Mobile application and cloud deployment for large-scale real-world adoption.

B. Application Domains

- Personalised digital healthcare and preventive wellness platforms.
- Hospital and clinical nutrition departments for patient dietary management.
- Public health monitoring at population level for nutritional epidemiology research.
- Corporate wellness programmes targeting employee health and productivity.
- Healthcare analytics and academic research in nutritional psychiatry.

IX. CONCLUSION

This paper presented NutriMood AI, an end-to-end intelligent healthcare framework that demonstrates the practical feasibility of predicting emotional well-being from nutritional and lifestyle data using machine learning. The system successfully integrates nutrition tracking, micronutrient deficiency detection, lifestyle monitoring, AI-driven mood prediction, personalised recommendation generation, and visual analytics within a single, cohesive web application. Experimental results confirm that nutrition and daily lifestyle behaviour exert a statistically significant and measurable influence on emotional wellness outcomes. Among the five evaluated classifiers, LightGBM achieved the highest mood prediction accuracy of 93% with an F1-score of 0.92, outperforming all alternatives with statistical significance. The ablation study further demonstrated that micronutrient features and lifestyle indicators are both indispensable components of the prediction pipeline. These findings validate the core hypothesis of this research and lay a concrete foundation for future work in AI-assisted personalised healthcare, nutritional psychiatry, and emotionally-aware wellness systems.

REFERENCES

[1] L. Chaves et al., "Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review," Nutrients, vol. 16, no. 7, 2024.

[2] D. Kirk et al., "Machine Learning in Nutrition Research," Advances in Nutrition, vol. 13, no. 4, pp. 1200–1215, 2022.

[3] "Artificial Intelligence in Nutrition and Dietetics: A Comprehensive Review of Current Research," PMC/PubMed, 2025.

[4] "A Scoping Review of Artificial Intelligence for Precision Nutrition," Advances in Nutrition, 2025.

[5] "Personalized Nutrition Recommendation System Using Machine Learning and Deep Learning Algorithms," Springer LNNS, 2024.

[6] "AI Nutrition Recommendation Using a Deep Generative Model and ChatGPT," Scientific Reports (Nature), 2024.

[7] "AI-Driven Personalized Nutrition: RAG-Based Digital Health Solution for Obesity and Type 2 Diabetes," PMC, 2024.

[8] "OBESEYE: Interpretable Diet Recommender for Obesity Management using Machine Learning and Explainable AI," arXiv, 2023.

[9] "Predicting Mood Swings in Women Using Machine Learning on Metabolic, Menstrual and Lifestyle Indicators," Frontiers in Global Women's Health, 2026.

[10] "Machine Learning-Based Prediction of Mental Well-Being Using Health Behavior Data from University Students," Bioengineering, 2023.

[11] "Machine Learning Techniques to Predict Mental Health Diagnoses: A Systematic Literature Review," Clinical Practice and Epidemiology in Mental Health, 2024.

[12] "Lifestyle Predictors of Depression and Anxiety During COVID-19: A Machine Learning Approach," PMC, 2022.

[13] "Predicting Unreported Micronutrients From Food Labels: Machine Learning Approach," JMIR mHealth and uHealth, 2023.

[14] "NutrifyAI: An AI-Powered System for Real-Time Food Detection, Nutritional Analysis and Personalized Meal Recommendations," arXiv, 2024.

[15] "ChatDiet: Empowering Personalized Nutrition-Oriented Food Recommender Chatbots through an LLM-Augmented Framework," arXiv, 2024.