Mood Meets Meal: An AI Framework for Emotion-Centric Nutritional Recommendations

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***Abstract*—Personalised nutrition stands out as a vital aspect for health, but existing food recommendation technologies fail to recognize emotional factors. This study presents a modern framework that uses AI technologies to provide personalized meal recommendations for targeted emotional states of users. The system measures food compatibility through an analysis of nutrient requirements that vary according to mood through its use of facial emotion recognition and machine learning combined with nutritional science. We built an emotion detection model that operates on mobile applications where users can access a recommendation engine, which was trained through Random Forest on our selected food-nutrition dataset. The system reached 94.9% Top-1 Accuracy on the reduced dataset while showing correlations between key nutrients with particular emotional states. Additionally, user-specific preferences functioned as a personalization feature which worked independently from any need for retraining processes. The mood-based recommendation system aimed to enhance user satisfaction through nutritional choices that lead to mental health potential benefits. This research enhances knowledge about affective computing in food informatics as it establishes possibilities for emotion-based AI applications in people's everyday routines.**

***Index Terms*—Meal Planning, Personalised Nutrition, Emotion Detection, Recommendation System, Machine Learning.**

I. Introduction

According to previous studies, people tend to select their food based on both physical body needs and emotional states [1]. People who feel negative emotions tend to choose rich carbohydrates such as sweet foods and sugary beverages, but those in positive moods prefer eating healthier, such as vegetables, fruits, and protein foods. Research shows that everyday stress, together with interpersonal conflicts, triggers negative moods which influence how people eat while affecting their emotional management abilities [2].

Present-day food recommendation programs fail to consider users' emotional states, yet there is substantial scientific proof of the connection between emotions and dietary selection. The lack of attention to user emotions deprives them of robust solutions that could simultaneously benefit their actual and emotional health. Most such systems continue to operate with static preference frameworks that do not support real-time adjustments according to the affective states of users [3], [4].

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"Mood Meets Meal" proposed an AI-based food recommendation technology that employs emotional facial detection and nutritional system analysis. The system utilizes a Random Forest regression algorithm trained on scientific nutrient-emotion relationships to calculate food compatibility scores, combined with the system to detect user moods by using facial expressions. Users can access this model through its mobile application, which blends React Native and Flask technologies to generate emotional diet recommendations in real time.

The study integrates emotional computing techniques into nutritional science while offering an innovative combined perspective on food information technology. The system identifies users' feelings automatically, then connects emotional states to custom nutrient data through its built-in functionality for food recommendation without requiring additional training. Synthetic data augmentation methods make the system more reliable and enable it to understand various situations.

The contributions of this paper are:

1) Developing a system that **recognizes emotions** to recommend foods based on what best matches the user's **mood**, **nutritional science**, and **nutrient prioritization**.
2) Designing a **scoring method** that determines how food matches user feelings according to the recommended nutritional intake.
3) Creating a **recommendation system** that uses a scoring method with **machine learning models** (regression, ranking, and classification), which got a Top-1 accuracy of **94.9%** on the reduced dataset.
4) Integrating the systems into **Mood Meets Meal**, a cross-platform mobile application, that delivers **personalized nutrition recommendations** in **real time**.

II. Related Works

The advancement of emotional food suggestions results from integrating emotion detection, machine learning algorithms, and nutritional research. The next section analyzes research about (II-A) mood-based food recommendation systems, (II-B) machine learning for personalised nutrition, and (II-C) emotional influences on food decision-making behavior.

A. Mood-Based Food Recommendation Systems

Food recommendation systems to date have depended mainly on users providing their emotional states manually for integration. For instance, users of the Mood-Based Food Recommendation System developed by Sreenidhi Institute of Science and Technology pick their mood directly before the system uses K-Means clustering and collaborative filtering to present restaurant recommendations [5]. This development stands as an advancement in emotion-aware systems, but fails to detect emotions automatically and does not incorporate the nutritional properties of food ingredients.

Several systems focus on enabling users to assign mood tags to food items [5], thus making it possible to find comfort foods connected to particular emotions. The current platforms operate using heuristic methods, yet they do not include machine learning technology to recognize sophisticated associations between people's emotional conditions and nutritional value. The systems choose taste and availability over lasting psychological benefits and long-term health results.

B. Personalized Nutrition Using Machine Learning

Artificial intelligence algorithms study monitoring nutritional advice toward individual needs by considering biological elements and medical specifications. Various studies adopted from machine learning research explore the usage of physiological and clinical data points for personalized dietary advice delivery. Researchers have utilized three algorithms, including Random Forest [6], Support Vector Machines [7], and neural networks, to produce dietary plans which incorporate data about BMI and dietary restrictions, allergies, and disease risk factors [3], [4]. Researchers have developed predictive models that unite to create personal diabetic meal plans and weight reduction meal suggestions that align with user specifications.

Such systems achieve success by working with pre-established user characteristics, which remain static despite lacking real-time detection of dynamically inferred emotional states. The present systems demonstrate limited capacity to apply knowledge from one situation to new ones, since they struggle with psychological or behavioral datasets.

C. Experimental Studies on Mood-Driven Food Choice Behavior

The impact of emotional states on consumer food preferences became a focus of behavioral studies before this research. Through their studies, leaders in controlled experimental analysis established that people in positive moods will opt for healthful foods, yet participants in negative moods choose high-calorie, hobby foods [1]. The studies examine mood as a psychological element shaping food conduct but do not analyze nutritional values. This study goes beyond behavioral preferences by exploring the relationship between emotional states and biological needs so that patients can get suitable nutritional value based on their specific health requirements. The system transitions from mood-based food selection to mood-suitable nutritional prioritization because of this development, which creates the foundation for emotion-aware recommendation algorithms.

III. Methodology

The aim of our research is to provide a method that connects affective computing and nutritional science, as well as machine learning, for personalized food recommendations according to emotional states.

We create a system consisting of four key components:

1) The user's emotional state is identified through a **simplified recognition method**.
2) The determination process for preferred nutrients depends on their emotional regulation capability, which establishes **mood-focused nutritional targets**.
3) **A scoring system** is developed to assess whether the food items match the emotional requirements.
4) A **real-time personalized suggestion model** based on machine learning is the last component that integrates within the system architecture.

The succeeding portions offer comprehensive explanations about every element of the proposed framework.

A. Emotion Recognition

Here, we consider two mood detection methods: psychological questionnaires and facial expression analysis. Firstly, a shortened version of the Mood and Feelings Questionnaire (MFQ) [8] was proposed for self-assessment due to its simplicity and accessibility. However, we discovered that the MFQ detects depressive and anxious states but shows weak performance regarding positive and neutral emotional states. Consequently, the system adopted a pre-trained facial emotion recognition model from Hugging Face [9]. Such an approach delivered quick, non-invasive results to the problem without demanding psychological specialists or large-scale data collection. Development of recommendation logic received primary focus after the project team employed a pre-built model, which preserved sufficient inference quality since emotion detection was not a main development objective [10].

B. Nutritional Prioritization Based on Emotional States

Previous psychological and physiological studies show that emotional states create various health outcomes [11], [12]. For instance, sadness results in decreased vitality and motivation, along with low serotonin and dopamine levels that support emotional stability [11]. In contrast, the scientific view of happiness sees it as a biochemical equilibrium and a dual goal of nutrition and behavior [12].

On the other hand, unregulated fear sets off protective biological processes while creating oxidative stress problems that lead to long-lasting physical results [13]. Self-disgust pertains to an escalation of protective mental mechanisms into depreciating one's self-value, and this pattern links to increased likelihood for depression along with anxiety development [14]. Even stable emotional states need supportive measures to prevent changes in negative affect, especially when people manage their diet and lifestyle patterns [12].

Finally, a surprise produces emotions that fall between joy and fear and triggers immediate physical adjustments, including adrenaline spikes and changes in heart rate, when the brain analyzes new stimuli [15].

Table I presents the related nutrients for each emotion with detailed information about the most suitable choices as well as their psychological effects and physiological roles.

TABLE I
PRIORITY NUTRIENTS BY EMOTIONS

Emotion	Top Priority Nutrients	Primary Functions
Sad	Polyunsaturated Fats, Vitamin D, Protein, Vitamin B6, Vitamin B12, Magnesium, Zinc	Supports serotonin production, reduces inflammation, and improves depressive symptoms [16]–[20]
Angry	Magnesium, Vitamin C	Regulates GABA and adrenal function, helping reduce stress and emotional reactivity [16], [20]
Fear	Magnesium, Polyunsaturated Fats, Vitamin B6, Vitamin 12, Vitamin C	Calms the HPA axis and oxidative stress response, supporting emotional balance under fear [16], [19], [20]
Disgust	Dietary Fiber, Magnesium, Zinc, Vitamin B6	Restores gut-brain balance, relieves visceral tension, and promotes mucosal healing [16], [20], [21]
Neutral	Carbohydrates, Protein, Vitamin B1, B2, B5, B6, B12, Magnesium, Zinc, Iron	Maintains energy, cognitive clarity, and neurotransmitter synthesis [18], [20], [22]
Happy	Protein, Carbohydrates, Vitamin D, Polyunsaturated Fats, Magnesium	Enhances serotonin synthesis and sustains emotional well-being [16]–[18]
Surprise	Carbohydrates, Vitamin B1, B2, B3, B5, B6, B12, Protein	Boosts alertness and cognitive performance through stress adaptation and dopamine support [20], [22]

The prioritization framework is the foundation for the system's personalized food scoring in the system. Within this model, the recommendations automatically adjust to fit both the health requirements and the emotional needs of the user at any given point. The system includes age-based recommended nutrition guidelines following the regional dietary standards to provide dietary suitability across age groups [23], [24].

C. Nutrient-emotion compatibility scoring method

We created a scoring method to measure the compatibility between food items and user mood states after developing emotional state nutrient plans. The recommendation engine implements its fundamental operational principle through this approach so it can provide rankings of meals that balance nutritional value against therapeutic benefits as they relate to specific moods.

The proposed system **quantitatively** evaluates **nutrient emotion alignment**, which previous recommendation systems **failed to establish** [3]–[5].

A food item receives a description through nutritional profiling that shows quantities of macronutrients, such as fat, carbohydrates, sugar, and micronutrients, such as vitamins, as well as dietary elements. The system retrieves nutrient lists for each emotion and assigns weight values based on their significance. This uses linear weight distribution that assigns 1.0 priority to its primary nutrient, followed by decreasing weights at lower priorities down to 0.1. The weights undergo normalization because this prevents unfair distribution of contributions between nutrients. The total weight value equals 1.0 for balanced nutrient participation.

The scoring process consists of three steps:

1) Standardization by Recommended Intake: Research on nutrient content in food items relies on daily recommended intake data that evolves according to human age groups [20], [21]. This allows the model to assess whether a nutrient is within a beneficial range for the user's demographic.

2) Suitability Factor Calculation: A suitability factor calculates the alignment between food nutrient values and recommended intakes for every nutrient in the emotional priority list. The calculation system both gives negative scores to amounts beyond recommended levels and generates positive scores for values near recommended amounts. The suitability factor is defined as (1):

$$\text{factor}_i = \begin{cases} \max\left(0.1 - \dfrac{\left(\dfrac{\text{actual}_i}{\text{ideal}_i} - 2\right)}{3}, 0\right) & \text{if actual}_i > 2 \times \text{ideal}_i \\ 2 \times \dfrac{\text{actual}_i}{\text{ideal}_i} & \text{if actual}_i < 0.1 \times \text{ideal}_i \\ 1 - \min\left(1, \left|\dfrac{\text{actual}_i - \text{ideal}_i}{\text{ideal}_i}\right|\right) & \text{otherwise} \end{cases} \tag{1}$$

Note: The suitability factor penalizes large deviations from the ideal nutrient intake and rewards values close to the ideals

3) Total Compatibility Score Computation: The final score is obtained by summing the weighted suitability factors across all prioritized nutrients, then normalizing the score to a 0–10 scale for interpretability as (2) shown:

$$\text{score} = \sum_{i=1}^{n} (\text{normalized\_weight}_i \times \text{factor}_i) \times 10 \tag{2}$$

Note: The final score ranges from 0 to 10 and reflects how well a food item fits the prioritized nutritional profile for a given emotional state.

The approach solves the problem of handling multiple nutrient limits within a system that is simple to understand and well-adjusted to diet registry information.

The scoring system allows the recommendation model to conduct impartial assessments of food items through a standardized mood-nutrient evaluation system. The method implements punishment for deviating nutrient amounts while using the recommended dietary intake guidelines as its reference point for accurate assessment. This scoring function remains a base point for assessing the performance of machine learning models when they are presented in upcoming sections.

D. System Architecture and Model Design

The system operates as an intuitive human-oriented platform which connects personalized nutrition to the emotional states of its users. The system perfectly records users' feelings and analyzes nutritional information and automatically produces customized food suggestions while operating in real-time. The developed system uses mobile programming frameworks along with strong machine learning capabilities. The predictive models successfully forecast food compatibility, thus converting raw algorithms into a compassionate companion which understands food-nourishment correlations alongside mood changes.

1) System Architecture: A client-server architectural design controls the entire system as represented in Fig. 1, which divides network operations into frontend and backend, and Artificial Intelligence services. The system used React Native to develop its mobile application frontend that supported deployment for both iOS and Android platforms. Flask operated as the platform behind the backend to implement both request handling protocols and image processing functions alongside recommendation response management.

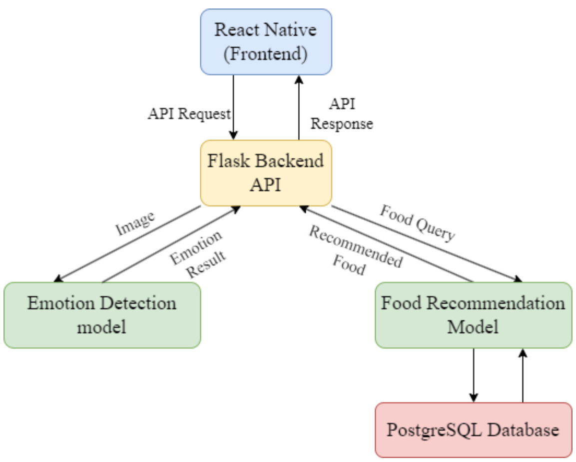

Fig. 1. System architecture: client-server design with separation of frontend, backend API, AI models, and database

User interactions begin with human face image capture or selection through the mobile interface. The system forwards the image to the backend facility for analysis through a Vision Transformer [25] implementation that analyzes the face and generates results from a list of six emotional states comprising **happy, sad, angry, fearful, disgusted, surprised,** and neutral. The recommendation engine receives both the detected emotion and user contextual attributes, including age categories as well as meal-time data points (e.g., "Breakfast", "Lunch", "Dinner", "Snack").

The backend retrieves the nutritional profile of all available food items from a structured database and calculates compatibility scores using the method described in Section III-C. Based on the resulting scores, the system selects its recommendations from the items with the highest ranking positions. Optionally, the system applies additional filters to recommendations for individual users depending on their dietary requirements or personal preferences.

2) Model Design and AI Components: A system for improving recommendation accuracy applies various machine learning models to synthetic dataset information from real-world food nutrition databases. The AI pipeline has three essential elements, which comprise:

- **Regression Model:** Predicts the compatibility score of a food item based on nutritional attributes, emotion, meal type, and user age group. The Random Forest Regressor was selected because it provided both interpreting capabilities alongside resistance to outliers.
- **Ranking Model:** The system teaches itself to organize food items through the Random Forest Regressor according to their estimated value for users based on emotional states and nutritional needs. The output list gets adjusted through this model to show emotionally suitable options first.
- **Binary Classification Model:** The system differentiates between meals that are appropriate for particular emotional states and ones that are not by the Random Forest Classifier. Robustness is achieved through this model design, which verifies unsuitable meal recommendations to stop their propagation.

The system employed data processing methods in combination with features that related emotional condition to nutritional factors to train its algorithms. All nutritional values received standardization treatment to maintain learning consistency across the system.

The combined algorithm system functions as a hybrid decision engine that utilizes AI forecast predictions together with scientific scoring rules from the compatibility model. The architecture includes modular APIs that will allow future integration between the system and menus from restaurants, together with wearable devices and user feedback cycles [26].

IV. Experiment And Evaluation

This part of the paper analyzes the model's technical capabilities since sufficient time and resources were unavailable for user-based evaluations to analyze user behavior more deeply, which will be addressed in future work.

A. Dataset and Preprocessing

Our team used two open-source datasets to test the system:

- The Food Nutritional Facts dataset [27] with 1,174 food items primarily from a variety of global sources, including beverages and processed foods. It provides detailed nutritional information such as fat, protein, sugar, and vitamins for each item standardized per 100 grams.
- Daily Food and Nutrition dataset [28] with 10,000 user dining records. Its information is based on a wide spectrum of dietary patterns from actual dietary guidelines and public databases rather than specific human participants.

The dataset was filtered down to focus on 34 nutrients linked to emotional control, and the foods were grouped into 7 categories: Meat, Fruits, Grains, Vegetables, Snacks, Dairy, and Beverages [29].

The nutrient measurements were changed to milligrams because the system needed current daily dose information. We removed unnecessary nutrients from the dataset and changed the names to make them easier to understand (e.g., Folate became Vitamin B11). The user interaction database received food type mapping from the nutritional records and meal-time distribution inspection for synthetic data organization support.

1) Synthetic Data Generation: Simulations for realistic situations with different mood states, mealtime, and ages they belonged to. A training method was applied to achieve uniform data distribution across emotional categories and meal types to avoid class dominance that could affect model training. Within each scenario, ten food item candidates received compatibility score computations through the scoring procedure outlined in Section III-C. The system also generated inverse scores to identify emotionally mismatched foods, which served as negative examples during model training. Additionally, future food recommendations use previous dietary ratings as a teaching tool for the system to understand comfort food preferences.

The training samples included encoded attributes, including emotion classification, along with age divisions and food categories, standardized nutrient values, and combination factors (e.g., "interaction_sad_Protein"). The dataset was divided into an 80%/20% training and testing split . All nutritional features were normalized using `StandardScaler()`, which is a `scikit-learn` library function that standardizes features to have zero mean and unit variance. This ensures all nutrient features are measured on the same scale, preventing bias during training and improving model stability.

2) Model Training and Evaluation: A set of three Random Forest models conducted tasks for regression analysis of compatibility scores while performing ranking of food items, followed by binary classification that categorized relationships as good or bad. All models used 200 estimators with a maximum depth of 10, and class balancing was applied in the classification model.

Evaluation metrics included:

- Regression: R^2 score = 0.9930, MSE = 0.0276
- Ranking: R^2 = 0.9699, MSE = 0.2436
- Classification: Accuracy = 99.9%, Precision = 0.998, Recall = 1.000, F1 = 0.999

To evaluate both model fit and generalization performance, learning curve analysis was applied to the regression, ranking, and classification models. This method provided cross-validation scores based on incremental training sizes, rather than using fixed 5-fold cross-validation. The classification and regression models achieved strong performance, with final cross-validation scores of 0.999 and 0.992, respectively, and a minimal gap between training and testing performance. Although the ranking model exhibited signs of overfitting (CV score = –0.235), it was only used for reordering filtered results, so such deviation was acceptable at this stage of deployment.

The analysis using SHAP values showed that emotional nutrient interactions represented the strongest predictive elements for both regression and classification statistics (e.g., "interaction_angry_Magnesium", "interaction_disgust_Dietary Fiber"). Notably, the analysis showed **magnesium** and **omega-3** nutrients consistently appearing among the two most important elements that impact emotions, which are associated with sadness and fear.

3) Comprehensive Evaluation: The system assessment required 294 test cases for all possible pairings of emotions along with age groups, meal times, and food types. Two datasets were tested: the full set (1157 food items) and a reduced set (top 230 items used in the app). Results were shown in Table II.

TABLE II
SYSTEM EVALUATION RESULTS ON FULL (1157 FOOD ITEMS) AND REDUCED (TOP 230 ITEMS USED IN THE APP) DATASET

Dataset	Top-1 Accuracy	Top-3 Overlap	Avg. Processing Time (sec)
Full	87.07%	74.72%	4.93
Reduced	94.90%	86.05%	0.85

The reduced dataset was constructed to simulate the practical constraints of a real-world mobile deployment environment, where it is impractical to include the entire dataset due to memory and computational limitations. To build this reduced set, approximately 230 food items were randomly selected while ensuring balanced representation across major food categories. This selection allows the system to be lightweight and responsive, which is critical for mobile applications.

Furthermore, the reduced dataset was evaluated using the same metrics as the full dataset to ensure fairness and model reliability. The model's performance on these smaller subsets verifies its capability to apply to real-world data samples and our consistent use of training and testing (80/20) partitions during development to prevent data leakage and bias.

The system registered better accuracy levels and executed faster when working on the downsized dataset, making it ready for real-time mobile application usage. These results confirm that the model performs efficiently and accurately in a resource-constrained environment, validating its readiness for deployment on mobile platforms.

V. DISCUSSION

Experimental outcomes validate how the proposed food recommendation system generates both nutritionally correct and emotionally suitable meal suggestions to the users. A reduction in dataset size led to an evaluation of **94.90%** correct first-choice recommendations, which confirmed that the machine learning model successfully learned to replicate the compatibility scoring method presented in Section III-C. This demonstrates the model's ability to generalize scoring patterns and simulate expert-designed evaluation rules. Furthermore, the system managed acceptable results when processing the full food database (Top-1 accuracy reached **87.07%**) while working with an enlarged food selection that showed the strength of the compatibility scoring methodology.

Although prior studies explored food recommendations with mood tagging or static user attributes [3]–[5], they were lacking in quantitative benchmarks and did not model nutrient-emotion alignment. In contrast, our model uses facial recognition and explainable nutrient scoring to personalize recommendations. While direct comparison is limited due to the absence of standard Top-k metrics in earlier works, our approach offers one of the **first empirically validated benchmarks** in this field.

Our system succeeds through its ability to combine psychological and biomedical knowledge alongside AI-driven scoring approaches. The feature importance analysis demonstrated that emotional factors and nutritional variables played a major role in predicting our system's accuracy and proving the effectiveness of its design. However, testing was done with synthetic data because no public emotion–food datasets were available at the time. Future work on emotional nutrition should focus on user interactions, cultural dietary patterns, and individual eating behaviors.

VI. Conclusion and Future Work

This paper proposed an emotion-aware food recommendation system that combines facial emotion recognition with explainable nutrient scoring. When tested on a reduced dataset, the model achieved **94.90%** Top-1 accuracy with an average processing time of **0.85 seconds** per recommendation (on Google Colab), demonstrating the feasibility of real-time deployment. Feature importance analysis revealed crucial predictive power of interactions between emotions and nutrients. While testing was based on synthetic data due to the lack of public emotion–food datasets, future work will focus on real-world validation, integration of multimodal emotion inputs (e.g., speech, sentiment, food images [30]), and adaptive recommendations based on cultural and individual emotional eating patterns.

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