MOBILE APPLICATION FOR FOOD RECOMMENDATION BASED ON USER'S MOOD USING AI MODELS

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ABSTRACT

Nowadays, AI is gradually changing the way people access information and make decisions, so the application of AI in personalized nutrition is becoming increasingly necessary. The thesis develops a method that applies AI to generate food recommendations according to user mood expressions. The essential part of the recommender system is the food recommendation model depends on machine learning algorithms for appropriate food choices from nutritional data and eating behavior; meanwhile, the facial emotion recognition model is selected from a pre-trained model on Hugging Face. Thus, this study applies primarily to the Random Forest algorithm to train a model to predict suitable foods based on nutritional parameters. In addition, to identify the relationship between emotions and nutrition, the study synthesizes scientific literature in the fields of psychology and nutrition. Ultimately, the project integrates these models through the integration of React Native as a frontend technology alongside Flask for the backend development.

AUTHOR KEYWORDS

AI-driven food recommendation system, Mood-driven dietary recommendation, Random Forest in Nutrition AI recommendations, Facial emotion detection for food selection, AI in health and nutrition informatics.

INTRODUCTION

1. Background

According to the study "Effects of daily stress on negative mood" in 1989, there are many factors that can cause stress in this life from gender differences, for example, women tend to have stronger negative mood reactions to personal problems such as traffic problems; however, men tend to be more affected by financial problems. In some cases, some factors can make women's moods better but make men's moods worse. Interpersonal conflicts from arguments between husband and wife, children, etc., have a significant impact on leading to negative moods and persistent stress has been shown to be related to poor mental health tolerance. In addition, the author also showed that mood will tend to improve immediately after a stressful event has just occurred (Bolger *et al.*, 1989).

Understanding when people overcome or release negative states, they will have a quick recovery to stabilize their emotions, along with being inspired by studies in the study "Better moods for better eating?: How mood influences food choice" in 2014 related to letting users choose healthy food or a dish according to their personal preferences that match their current mood is negative or positive. Furthermore, most people select carbohydrate-rich foods such as candy and sugary drinks to increase serotonin production during times of negative feelings. Conversely, when happy, they tend to choose energy-rich and nutritious foods such as fruits, vegetables and proteins (Gardner *et al.*, 2014).

Therefore, I implemented this thesis as an additional potential solution to suggest which foods can really help improve negative moods or are suitable to maintain and stimulate positive states according to scientific research about the nutrients in the ingredients of each dish combined with a little personal preference of the person. From there, the results obtained after the project can partly support further research on the food selection behavior of users for each specific type of mood in the future.

2. Problem Statement

Understanding different moods, the factors and the effects of those moods on human health. The problem is that I need a system that can detect human emotions. In terms of expertise, as an IT student, I do not have the expertise of psychologists to be able to easily diagnose and define human emotions, which are extremely complex. Therefore, the core problem is the lack of accuracy in choosing emotion recognition options.
However, the above problem can be solved if using the support of current AI models. The restricted capabilities of algorithms result in another problem because they have trouble differentiating intricate emotional cues, especially when faced with various human emotional expressions. Since the AI model can only predict emotions based on the data collecting and training process of humans, it is impossible to ensure that the process has been standardized from research in psychology.
In addition, concerns about choosing the right dataset along with an algorithm suitable for the dataset and the project's need for suggesting dishes based on mood using an AI model are also difficult problems. Therefore, the solution was that I needed to determine from the beginning the reason, criteria for the dataset, the necessary data type and which algorithm is suitable. This leads to the next problem based on the selected dataset, I must give methods on using which data type to research which ingredients in food would suit which mood of people.
Subsequently, current food recommendation applications are mainly based on personal taste and preferences, without fully exploiting the mood factor in food decision-making. Meanwhile, nutrition research indicates that feelings affect our selection choices regarding food. Therefore, the problem that needs to be solved is how to scientifically and effectively incorporate mood into the food recommendation process using AI.

Therefore, this study aims to explore and analyze the above problems in detail and propose solutions to improve the accuracy and applicability of the systems. Solving these problems would contribute to promoting the development and effective application of AI recommendation technology to identify human behavior depending on mood.

3. Scope and Objectives

The scope of this thesis is to develop a model that can suggest suitable food based on the analysis of the effectiveness of each nutrient in each dish for each type of emotion. This model will be trained using ML techniques on a public dataset containing the names of food with the quantification of nutrients in that dish per 100g of intake. Additionally, I also integrate a public model that has been studied to be able to classify certain emotions through facial selfies. All of this is integrated and built into a mobile application with a user-friendly interface, importantly, it can visualize the results of my research. The efficient project implementation process relies on my detailed plan that distributes tasks using the Project Timeline and Gantt chart and WBS (Appendix A-C).

The objective of this work is to analyze the relationship between mood and nutrients, combined with individual nutritional needs. Next, I need to create a dependable system with self-learning abilities to employ the appropriate algorithm for accurate mood-based dish suitability assessments. Finally, evaluation of the model performance requires analysis using accuracy, recall and precision alongside confusion matrix evaluation.

4. Assumption and Solution

The research requires many basic assumptions:

- Mood has an impact on food recommendation and this can be modeled using nutritional data.
- Emotion data from facial images can be used to identify mood.
- Random Forest model is a suitable algorithm to solve the food recommendation problem.

Solution for these assumptions above:

- Food and nutritional value data from a standardized dataset.
- Facial emotion recognition model available from Hugging Face.
- Training the food recommendation model using Random Forest.

RESEARCH METHODS

1. Method approach research

To conduct this research, I focused on understanding two important aspects, one is to find the most accurate way to determine the user's mood and the other is how to build a mood-based food recommendation model using AI. Firstly, I researched scientific papers on the relationship between mood and nutrients to build a theoretical background for shaping the method applied to model training. Secondly, I had to research ML algorithms that can be applied to my project needs such as Logistic Regression, Random Forest, Gradient Boosting, etc. to choose an algorithm that is truly suitable for the data source that I found from online scientific libraries such as Google Scholar, IEEE Xplore, PubMed, etc (Table 1).

Research Theme	Goal
AI-based food recommendation system	For reference to previous research on food recommendation systems.
Mood and nutrition relationship	To investigate the relationship between nutrition and emotions and the scientific study of the impact of nutrition on mental health.

Tolerable Upper Intake Levels / Recommended Dietary Allowances / Daily dosage of mood-enhancing nutrients	To determine the appropriate daily intake of each nutrient

Table 1. Research theme

2. Methods to detect user mood

There are many different methods to determine a person's mood, hence, I needed to consider and compare two main approaches that are suitable for a person with no psychological or medical expertise like me.
Since I originally planned to build a mobile application to be able to determine mood, I planned to apply the MFQ questionnaire - a validated questionnaire in psychology that can be easily accessed for free. However, to ensure the user experience of the application, I planned to use a short questionnaire consisting of only 13 simple multiple-choice questions that can only be answered true (0), false (2), sometimes (1) to calculate a score to determine mood. However, according to the research report on MFQ, the above questionnaire can only support me in calculating the score for depression, anxiety, anxiousness but does not give me a specific scale for each mood. At the same time, after studying them more closely, this method still cannot determine the mood from neutral to positive states (Schlechter *et al.*, 2023).

Instead, the alternative option I proposed was to use a pre-trained model on Hugging Face, which is capable of classifying emotions from facial selfies. Firstly, my decision to not train an AI model to classify emotions from images but just apply an existing model because this was not the main goal I aimed for this project. It also helps me optimize the time to complete this project. Finally, detecting a person's mood without the help of psychologists could consume too much time in the process of collecting data and training this model. In addition, due to the model's lack of accuracy, from a medical perspective, it could also reduce the performance of the primary model deployment process for this project (Jain, Shamsolmoali and Sehdev, 2019).

3. Food recommendation method depends on compatibility score

This method seems to be the core method for my thesis this time, synthesizing scientific studies on important nutrients for each mood, from which I proceeded to build food selection rules.
At first, I established the relationship between emotional states and appropriate nutrients with personalized nutritional needs by determining a list of priority nutrients for each emotion such as "sad", "happy", "angry", "disgust", "neutral", “fear” and "surprise" (Appendix D). For example, for the sad state, the system prioritizes foods rich in polyunsaturated fatty acids (omega-3), vitamin D, B vitamins and magnesium.

After determining the priority list, a weighting system helped identify the significance of different nutrients for my evaluation. The priority nutrient, which received Number one, earned the highest weight value of 1.0, while the remaining nutrients received decreasing weights ending at 0.1, resulting in a linear weight distribution. This number was then normalized by dividing the total to ensure that all contributions equaled 1 (Figure 1).

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$$\text{weights} = \text{linspace}(1.0,\ 0.1,\ n)$$

$$\text{total\_weight} = \sum_{i=1}^{n} \text{weights}_i$$

$$\text{normalized\_weight}_i = \frac{\text{weights}_i}{\text{total\_weight}}$$

Note: The weights vector decreases linearly from the highest priority nutrient (1.0) to the lowest (0.1), then normalized to ensure $\sum \text{normalized\_weight}_i = 1$.

Figure 1. Priority Weight Normalization Process

After that, I performed the calculation process by determining the nutritional recommended daily intake for each age group (Appendix E). For each nutrient in the priority list, the system compared the actual nutritional value of the food to the ideal value that had been determined for the corresponding age group. The ratio between the actual value and the ideal value was then used to calculate a suitability rating factor. This approach helped me because it handled the variance based on the degree of deviation from the ideal value.

Specifically, if a food contains more than twice the ideal value for a nutrient (ratio > 2), the system applies a decreasing penalty according to the formula (Figure 2): factor = max(0, 1 - (ratio - 2) / 3). The scoring system prevents foods with very high nutrient content from obtaining high scores because excessive nutrition is not beneficial. However, the penalty is less severe when nutrient content falls below 10% of recommended values, which leads to factor = ratio * 2. For values within the appropriate range, the factor is calculated as 1 minus the relative deviation from the ideal value: factor = 1 - min(1, |actual value - ideal value| / ideal value).

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

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

Figure 2. Nutrient Suitability Factor Evaluation

The methodology calculates nutritional points, which involves the combination of standardization weight and rating factor, followed by a 10 times multiplication to establish an understandable scale. The overall compatibility rating results from summing all points that each priority nutrient contributes to the score (Figure 3). The algorithm generates a number between 0 and 10 that measures food suitability according to the user's emotional situation. A higher score indicates should score better when their foods show improved compatibility.

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

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.

Figure 3. Total Compatibility Score Computation

Finally, the scoring process under this assessment evaluates nutritious elements in foods based on their composition against standard dietary recommendations. Such precision enables recommendations suitable for each user's emotional situation alongside their age requirements and nutritional specifications.

RESEARCH FINDINGS

1. Related Work

The Mood-Based Food Recommendation System developed by researchers at Sreenidhi Institute of Science and Technology focuses on suggesting dishes and restaurants based on users' moods (Gupta *et al.*, 2021). The system uses K-Means clustering for location-based restaurant grouping together with collaborative and content-based filtering methods in their recommendation process. Using pre-set mood choices users can initiate the system which supplies food recommendations together with popular ratings and restaurants in their vicinity. Moreover, the integrated method in my project deploys an AI-operational facial emotion recognition model to automatically extract users' emotions from pictures instead of depending on person-to-person input. My project deploys the Random Forest algorithm to evaluate nutritional ingredients for mood compatibility while their system places importance on restaurant ratings and location; indeed, my work focuses on mood-optimizing nutritional meal recommendations. At present their web-based platform leverages Flask and PyCharm whereas my mobile application solution implements React Native with Flask to deliver a user-friendly interface to users. In conclusion, my work is different from their system because it selects health-conscious meals that match users' nutritional requirements and emotional needs by using scientific approaches to mood-based dietary guidance.

2. Date Collecting and Preprocessing

Understanding that data collection and preprocessing play an important role in developing a food recommendation system based on users' emotional states. I utilized the ***Food Nutrition Dataset*** [1] to obtain 2,395 different food information (Vegesna, 2024). I actively filtered the dataset to 230 items because it enabled me to create specific recommendations for bakeries or café rather than generalized food predictions. In addition, to establish data structure I incorporated a new "Types" attribute which divided the 230 items across four groups: cake, drink, dessert and sweet. Despite the significantly reduced sample size, the greater specificity and homogeneity of the data can still effectively support the applied algorithm in determining the relationship between nutritional content and emotional states, especially in the context of sweet foods. In particular, the above dataset includes important nutritional parameters such as calories, fat, protein, carbohydrates, vitamins and minerals - all of which are key factors in determining the relationship between food and emotional states. In the preprocessing stage, I have given the data several cleaning and normalization steps to ensure the quality of the machine learning model. Firstly, the dataset is comprehensively inspected through methods such as "df.info()" and "df.describe()" to understand the structure and distribution

[1] https://www.kaggle.com/datasets/utsavdey1410/food-nutrition-dataset

of the data. The results show that the dataset consists of 37 columns with different data types (int64, float64, object) and no missing values.

Next, Unit conversions occurred following the procedure which changed grams (g) into milligrams (mg) measures for nutrients including fat, carbohydrates, protein, and fiber to achieve uniform measuring units. Then, the process of removing unnecessary columns was performed, retaining only 33 important information fields related to nutrient composition and food type.

Subsequently, to prepare for building the ML model, the text data was encoded using the "factorize()" method, creating a "food_encoded" column that converts food names into numeric values. After that, I employed a boxplot to identify outliers in the numeric data for assessing data quality visually, which highlighted the need for normalization, such as Sugars and Sodium (Figure 4).

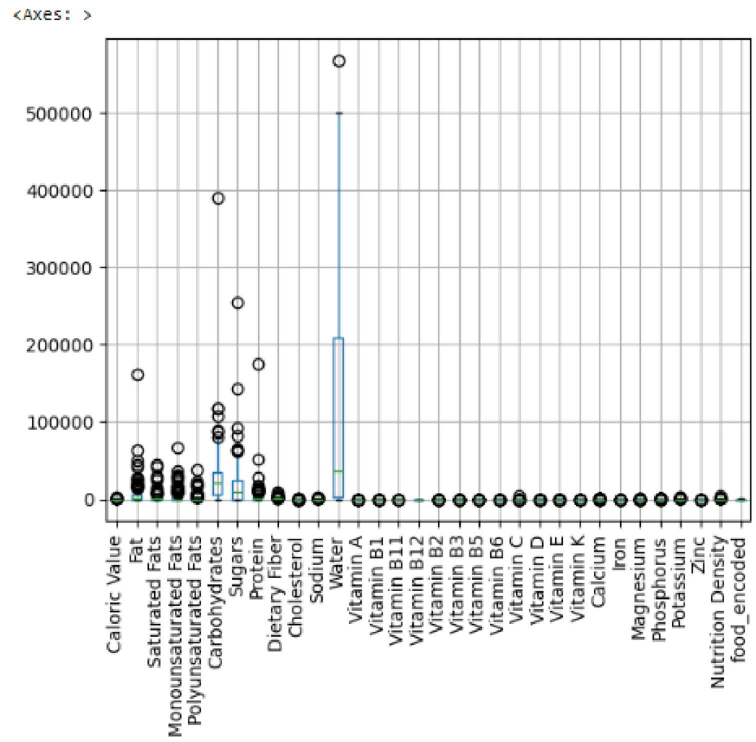


Figure 4. Boxplot of nutritional attributes

Finally, the modified dataset is saved as "food_nutrition.csv" so it can advance to the upcoming steps of AI model development. The preprocessing procedures generate structured data that prepares it for building a food recommendation system that personalizes nutritional experiences for users through AI technology.

3. The process of detecting facial emotion images

The emotion detection model ***(dima806/facial_emotions_image_detection)***[2] that I have chosen to apply to my project has been developed in a comprehensive and systematic process. After learning about the model through its description. This process begins with collecting and processing facial image data that represent different emotions and they are organized into training sets with clear emotion labels such as "happy", "sad", "angry", "fear", "surprise", "disgust" and "neutral".

During the data preprocessing process, they normalized the images through techniques such as cropping and resizing, normalizing the brightness, and applying random transformations (such as rotation, flipping, sharpening) to enhance the diversity of the data. This helps the model learn features that are invariant to small changes in shooting conditions.

In addition, when training the model, they applied the previously trained VIT architecture with the identifier ***(google/vit-base-patch16-224-in21k)***[3]. This model was fine-tuned on a facial emotion dataset with 7 different emotion classes. The model reached 91% accuracy after 25 training epoch applications (Figure 5-6). Furthermore, the confusion matrix code shows that the model works well on all 7 types of emotions, especially the emotions "disgust" and "surprise".

Classification report:

	precision	recall	f1-score	support
sad	0.8394	0.8632	0.8511	3596
disgust	0.9909	1.0000	0.9954	3596
angry	0.9022	0.9035	0.9028	3595
neutral	0.8752	0.8626	0.8689	3595
fear	0.8788	0.8532	0.8658	3596
surprise	0.9476	0.9449	0.9463	3596
happy	0.9302	0.9372	0.9336	3596
accuracy			0.9092	25170
macro avg	0.9092	0.9092	0.9091	25170
weighted avg	0.9092	0.9092	0.9091	25170

Figure 5. Facial Emotion Image Model Classification Report

2 https://huggingface.co/dima806/facial_emotions_image_detection

3 https://huggingface.co/google/vit-base-patch16-224-in21k

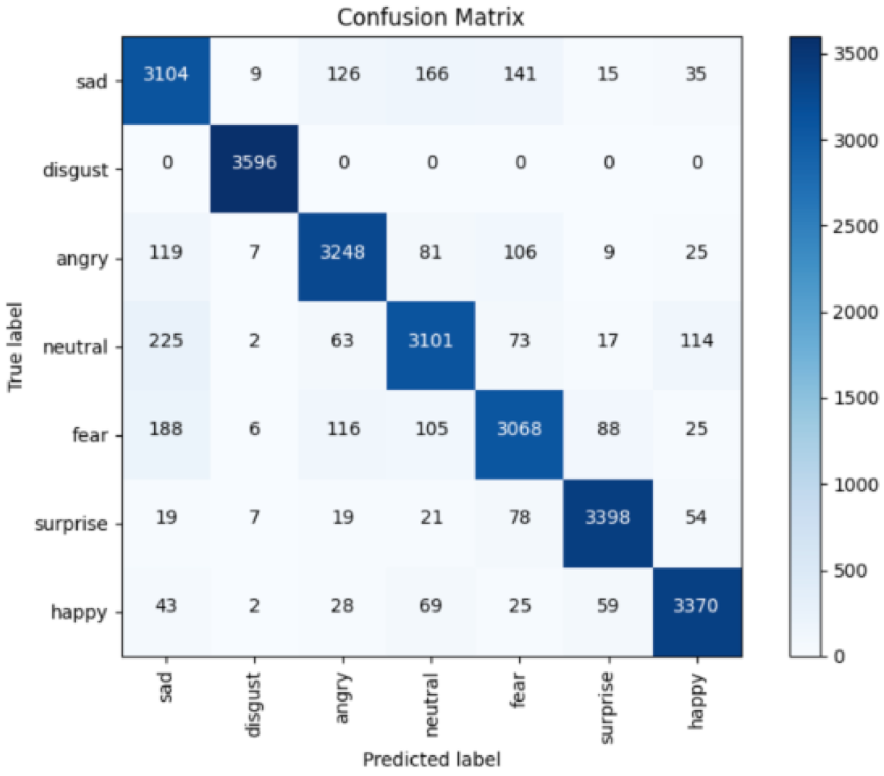


Figure 6. Facial Emotion Image Model Confusion Matrix

4. Nutrients related to mood and their recommended daily intake

Each emotional state is closely related to a certain group of nutrients. Below are the substances that are characteristic of each emotion and the effectiveness that has been studied separately along with the priority level of each substance for each emotion. The conclusions below will be partly my suggestion because there is no research expert to support me to confirm whether my conclusions are correct or not because not all studies on nutrients mention the name of the mood that is suitable for certain nutrients. Especially uncommon emotions such as "surprise" or "disgust". However, because this thesis is built as a proposal for further research, these proposals can be easily adjusted by synthesizing everything with my logic and basis, from which after consulting with experts related to this field, it is possible to support the adjustment of each index more accurately.

4.1. Nutrients and mood according to emotional state

People experiencing sadness show decreased vitality, diminished drive and reduced serotonin and dopamine levels in their system (Kitayama and Park, 2017). Therefore, my suggestion focuses on “emotional stimulation” and biochemical support. Evidence shows that the anti-inflammatory benefits of polyunsaturated fats (omega-3 EPA/DHA) justify their selection as the first-place treatment for depression. Next, Vitamin D follows, as it activates serotonin synthesis via TPH2 gene regulation. Then, Protein, which is rich in tryptophan, is ranked third due to its role as a serotonin precursor, especially effective when consumed with carbohydrates. Vitamin B6 and B12 are included for their coenzyme functions in synthesizing mood-related neurotransmitters. Both magnesium and zinc work together to regulate GABA function in the nervous system but zinc additionally aids NMDA receptor activity to reduce neuroinflammation that promotes emotional recovery.
Meanwhile, happiness is a state of biochemical harmony (Steptoe, 2019), and the nutritional goal is to “maintain” this

positive state. Hence, Protein (with tryptophan) ranks first, supporting serotonin synthesis when paired with carbohydrates, which themselves are ranked second for promoting tryptophan uptake into the brain. In addition, one of the following priority nutrients is Vitamin D because it helps control serotonin levels and minimize inflammation. The consumption of polyunsaturated fats (Omega-3 PUFAs) delivers two benefits to improving emotional control. Magnesium helps achieve relaxation status and regulates brain chemicals. The group of nutrients forms a synergistic system that bolsters and maintains biochemical processes of positive mood.

On the other hand, the activation of defensive neural mechanisms alongside oxidative stress starts after experiencing fear (anxiety) (Ghaemi Kerahrodi and Michal, 2020). At this point, I suggested "calm and restore balance." strategy. Firstly, Magnesium ranks first because of its direct role in reducing anxiety through GABA enhancement and HPA axis modulation. Polyunsaturated fats (Omega-3 PUFAs) take third priority because they decrease cortisol levels and enhance resilience. The positioning of Vitamin B6 and B12 justifies that they aid neurotransmitter balance; meanwhile, Vitamin C ranks last by providing antioxidants to fight stress-induced inflammation. Ultimately, I believe that these nutrients apply their benefits toward controlling neurological activity along with physiological stress reactions in fear states.

The feeling of disgust, while it is like a self-protective mechanism, can evolve into self-disgust, contributing to depression and anxiety (Gao *et al.*, 2022). The nutritional response requires both "strong calming" and "gentle reactivation." Therefore, Dietary fiber stands as the top priority to both heal gut-related discomfort and strengthen the connection between the gut and the brain. Magnesium helps relax visceral tension and reduce nausea-like responses. After that, Zinc supports mucosal repair and gut-brain recovery. Finally, Vitamin B6 helps produce GABA while possibly decreasing intestinal discomfort. The active components unite their effects to restore overall comfort while promoting positive reactions to distress.

Subsequently, the neutral state may seem emotionally stable, but it also needs to maintain positive neutral emotions through eating to help prevent negative emotional fluctuations (Steptoe, 2019). Carbohydrates stand first on the list for delivering sustained glucose that sustains brain operation. Protein ranks second for its amino acid supply critical to neurotransmitter synthesis. Next, energy metabolism and cognitive clarity depend on all the nutrients within the Vitamin B complex which includes B1, B2, B3, B5, B6, B12. Neurochemical balance together with stress buffering emerges from Magnesium and Zinc consumption but Iron enables oxygen transport and increases attention and cognitive performance.

Another point is surprise which lies between fear and joy, often changes heart rate, increases adrenaline slightly, and temporarily throws the brain out of balance to adapt to new information (Jang *et al.*, 2015). The method needs a balance between "stabilization and light modulation." So, simple carbohydrates rank first for delivering immediate energy to support alertness and cognitive readiness. The next sequence includes Vitamin B complex (B1–B6, B12) because they influence both energy metabolic functions and neurochemical processes in situations of acute stress. Then, Protein rich in tyrosine is third, as it promotes dopamine and norepinephrine synthesis, boosting cognitive performance. Lastly, Vitamins C and D control the response of the neuroimmune and buffer emotional overstimulation while protecting emotional reactions to unexpected situations.

When someone gets angry their sympathetic nervous system activates leading to an increase in cortisol and heart rate and blood pressure levels that could result in health damage when sustained (Smith *et al.*, 2004). Therefore, the focus is to "calm the system." Magnesium is prioritized first for its GABA-enhancing and anti-excitatory effects. Vitamin C stands as the second most valuable nutrient because it helps maintain adrenal function and reduces oxidative stress to regulate anger-related physiological reactions. The combination of these factors develops into an emotional de-escalation method.

In conclusion, all the details from priority level, and effectiveness of each nutrient have been summarized by me according to each source in Appendix (Appendix D).

4.2. Recommended daily intake

According to the parameters of "Review of recommended energy and nutrient intake values in Southeast Asian countries" in 2023, the author helped me statistically calculate the recommended intake for each nutrient I used in the dataset to train the model (Tee *et al.*, 2023). However, these numbers only focus on the index of Southeast Asians from many different countries with many different age groups such as infants, children, adolescents, adults. Therefore, I had to combine the reference of the study "Recommended Dietary Allowances should be used to set Daily Values for nutrition labeling" in 2006 which provided additional recommended nutritional numbers suitable for Americans and Canadians or scientific sources on the tolerable upper intake level of EFSA Panel on Nutrition to come up with an appropriate number that is synthesized by all documents and divided into two main age groups: children (< 16 years old) and adults (>= 16 years old) (Murphy and Barr, 2006) . Of course, this number will be given from the highest quantitative recommendation or suitable for the dataset. In addition, during my research I noticed that for macronutrients such as "Fat", "Carbohydrates" and "Sugars" there is no specific recommendation but rather a convention from their respective energy from the total daily calorie requirement (Godos et al., 2020; Tee et al., 2023). Specifically, fat is supposed to account for 35% of total calories, carbohydrates 65% and sugars 10% (Figure 7).

$$\text{Nutrient (mg)} = \frac{\text{Caloric Value} \times \text{Percentage}}{\text{Caloric Density}} \times 1000$$

Figure 7. Conversion Formula from Caloric Ratio to Milligram Intake

Thus, I converted the calorie contribution to milligrams by applying the known calorie density: 9 kcal/g for fat, 4 kcal/g for carbohydrates and sugars. The result was then multiplied by 1000 to express the value in milligrams. For nutrients that are mentioned only once in a single document, I will default to using that number as the recommended value without dividing by the average, or for nutrients such as water that are hardly mentioned in any document, I will default to not limiting the absorption of that substance because if absorbed in large amounts, it will not significantly affect health, such as doctors always advise patients to drink a lot of water (Appendix E).

5. Training AI food recommendation model

These experiments of building a food recommendation system based on the user's emotional state was carried out through a comprehensive machine learning model development process, with Random Forest as the main algorithm (Vaishnavi *et al.*, 2024). Therefore, I conducted a thorough research and implementation process to create a system that can analyze the correlation between emotions and nutritional needs based on scientific grounds. From the application of the model to identify emotions through selfies that I mentioned above, only seven types of emotions ('sad', 'happy', 'angry', 'disgust', 'neutral', 'angry' and 'surprise') can be confirmed, along with the method of food recommendation based on the compatibility score mentioned in the previous chapter.

I chose the Random Forest algorithm over other algorithms such as SVM, Neural Networks or KNN for several reasons (Martinez-Gorospe *et al.*, 2021). Firstly, the Random Forest algorithm processes non-linear data samples alongside diverse variable relationships without complicated preprocessing. Secondly, Random Forest provides better transparency than Neural Networks because it shows feature importance through which users can comprehend the model's decision-making process across its execution. Thirdly, the processing of categorical variables remains straightforward through Random Forest since it does not need complex one-hot encoding techniques. Additionally, the model demonstrates resistance to outliers in addition to handling noisy data without a data normalization stage while effectively working with highly correlated features – traits that frequently exist in nutrition datasets.

A comprehensive evaluation of the recommender system utilizes standard classification metrics along with overall accuracy measures, confusion matrix data and regression-specific metrics including MSE and R^2 (Jubeile Mark Baladjay *et al.*, 2023). The combination of these metrics provides an authentic depiction of how the model performs at prediction and how users can practically benefit from it.
A confusion matrix provides detailed insights for classification results through its organization of predictions into True Positive (TP) and True Negative (TN), plus False Positive (FP) and False Negative (FN) categories for precise misclassification diagnosis.

MSE evaluates the squares of average value differences between forecasted and actual readings in regression models, but R^2 determines the extent to which predictive values match the original data pattern. A predictive model features strong predictive power when its R^2 value is close to 1.0.
Additionally, feature importance analysis determined the principal inputs that influenced decision-making in classification, together with regression models (Jubeile Mark Baladjay *et al.*, 2023). The classification model depended heavily on features of emotion, age group and meal type, whereas the regression model benefited most from nutrient-specific variables, including protein, sugar and caloric value.
Finally, the defined compatibility scoring function was implemented as a domain logic benchmark to evaluate model outputs according to user dietary targets and mood nutrition alignment. This reference ground-truth assists model accuracy

assessment by offering vital information that helps evaluate the match between automated predictions and scoring produced by expert specialists.

In case, the system provides two types of recommendations: mood-optimized (based on emotional state) and personalized (when the user specifies a nutrient they want to enhance), with the latter case enhanced by placing that nutrient at the top of the list and multiplying the overall score for the food by 1.5 times in the priority list as a flexible factor for the model to adapt to produce different results (Figure 8).

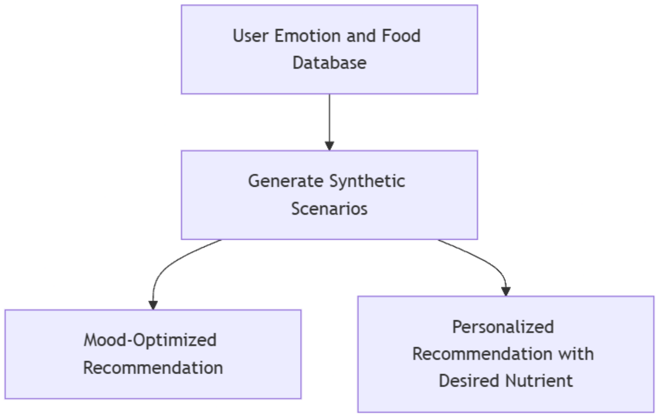


Figure 8. Recommendation Approach Flow

In addition to the mandatory step of applying a compatibility score along with nutrient priorities and daily intake recommendations, this experiment from 230 samples of different dishes of the dataset after preprocessing, I generated 2 synthetic datasets for training 2 AI models at the same time. The number of samples in these 2 datasets is not a predefined target but emerged naturally from the synthetic data generation process.

The code generates 1,000 recommendation scenarios and for each scenario, it generates multiple food options with corresponding scores. For the mood-optimized recommendations, this results in about 4 options representing the top 4 foods for each scenario. Personalized for recommendations requires a specific desired nutrient according to the user's personal preferences, resulting in fewer scenarios qualifying as foods for each applicable scenario. Since the more constraints you add, the fewer options qualify. Personalized recommendations must satisfy two sets of criteria (emotional state and specific nutritional addition), so fewer foods qualify than those that only satisfy emotional needs.

The feature generation process dynamically generates relevant features based on the input variables. The mood optimization model must only capture the relationship between emotion, age group, food type, and nutritional content. In contrast, additional features need to be implemented into the personalized model for depicting desired nutritional information using one-hot encoding for each possible nutrient (e.g. “desired_Vitamin_C” and “desired_Protein”) and measures of nutrient boosting effects (e.g. “desired_Calcium_boost”). The feature space expansion for personalized recommendations reaches almost double its initial size due to the inclusion of emotional state and nutritional requirement optimization criteria.

The Random Forest and Gradient Boosting methodologies were implemented to check the performance and accuracy. Training the Gradient Boosting Regressor and two models based on accuracy with the Compatibility score resulted in better performance according to my experimental results. This is because the model learns from the above features to predict the compatibility score by analyzing patterns in the data. Through learning the model understands which nutrients receive priority status for particular emotions (such as Magnesium and Polyunsaturated Fats and Vitamin B for Fear) and which foods offer the best nutritional satisfaction according to age group. The R^2 score and mean squared error are the measures I used to evaluate the model's accuracy in conjunction with the direct scoring from the compatibility score.

Two synthetic datasets were derived from the food nutrition database before the model training process started. The mood-optimized dataset contained 4,000 samples which offered individual food suggestions based on emotions but the balanced dataset included 2,720 samples that covered emotional states alongside nutrient requirements.

The mood-optimized model received 57 features, which were developed through meticulous application of feature engineering methods. "Supported_emotions.index(emotion)" indicated the encoded emotion features along with age group encodings through binary child/adult classification and food type encodings obtained from the original dataset and emotion-specific nutrient score features (e.g., "fear_Magnesium_score", "fear_Vitamin_B6_score"), accompanied by nutritional content normalizations (e.g., "norm_Caloric_Value", "norm_Protein"). The personalized recommendation model required a more complex feature space with 113 features, including all mood-optimized features plus one-hot encoded desired nutrient indicators ("desired_Vitamin_C", "desired_Protein", etc.), nutrient boost effect measurements ("desired_Calcium_boost", "desired_Magnesium_boost", etc.), and interaction features between emotions and desired nutrients. The function "prepare_direct_scoring_features()" utilized domain knowledge to create features that considered nutritional needs according to various emotional states.

Scikit-learn executed the Gradient Boosting Regressor model for training purposes. The key components included a configuration with 200 sequential trees, a conservative learning rate of 0.1 to prevent overfitting, controlled tree depth of 4, minimum samples required to split nodes set at 5, minimum samples at leaf nodes of 3, and using 80% of samples per tree for robustness, all with a random state of 42 to ensure reproducibility. The system used a train-test split (80-20) through "train_test_split()" of scikit-learn for model training, while fitting the mood-optimized model with ".fit(X_mood_train, y_mood_train)", then assessed results via "mean_squared_error", "R^2 score" and "mean_absolute_error". The training optimization function concentrated on reducing the error rate of the compatibility score because it determines how meals meet specific emotional state nutritional needs (Figure 9).

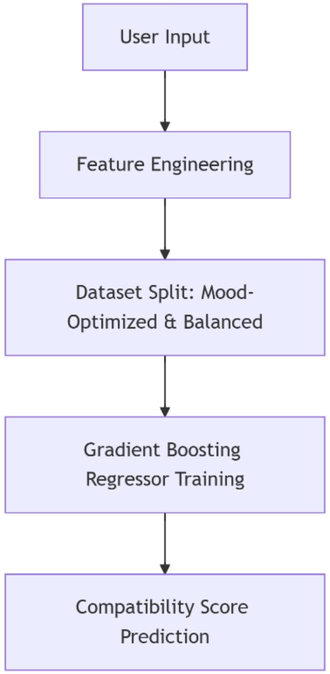


Figure 9. Pipeline for Mood-Optimized and Personalized Models

After training, the model and its mappings and feature names were serialized using joblib to ensure easy deployment in the recommendation system without additional training sessions. The mood-optimized model showed superb accuracy through its 0.9992 R^2 score and its low 0.0029 mean squared error value for predicting compatibility scores. The Gradient Boosting implementation showed the personalized recommendation model to achieve R^2 score of 0.9532 while maintaining a mean squared error of 0.2907.

The direct scoring method produced different results when analyzing the top 4 recommended foods alongside the metrics performance from both models, because of noticeable discrepancies between the outputs. The differences between model outputs indicate that, although mathematically accurate, the personalized model could learn patterns different from direct scoring algorithm priorities.

With the mood-optimized model recommendation results, there are some cases where the results are accurate with the direct scoring method, but not as accurate as the 99% accuracy results when I change the input. With the personalized recommendations results, the difference is even more obvious. The small number of 230 original foods in the sample likely produced overfitting problems. The large number of samples created (2,720) derived from an initial food database (230) could lead the model to learn specific patterns rather than true general relationships, which would then generate dissimilar recommendations when fed with different emotional states. In addition, this model is not practical when applied to a real project when I will definitely limit the amount of food dataset used in the application to demonstrate the ability and value of the AI model when it can learn rather than using the compability score feature directly to recommend, which would go against the purpose of the thesis.

In conclusion, realizing the problem, I will not apply this test to my application. However, this test can be improved in the future if more focus is placed on expanding the initial dataset to create more diverse training samples.

CONCLUSION

The research findings from this project enabled me to develop methods for AI-based food recommendation technology, which links nutrients to emotional states through scientific information. Additionally, I analyzed to select a suitable emotion recognition model along with an appropriate recommender system algorithm (Random Forest) to generate food recommendations based on enhancing both emotional health and food choices. Although the results I received from this experiment did not meet my expectations, I will experiment to train a model with a different approach in the hope of getting better results. Finally, I will deploy the development of a mobile application to visualize the results of my research on time.

REFERENCES

Bolger, N. *et al.* (1989) 'Effects of daily stress on negative mood.', *Journal of Personality and Social Psychology*, 57(5), pp. 808–818. Available at: https://doi.org/10.1037/0022-3514.57.5.808. [Accessed January 2025]

Gao, S. *et al.* (2022) 'Associations between self-disgust, depression, and anxiety: A three-level meta-analytic review', *Acta Psychologica*, 228, p. 103658. Available at: https://doi.org/10.1016/j.actpsy.2022.103658. [Accessed February 2025]

Gardner, M.P. *et al.* (2014) 'Better moods for better eating?: How mood influences food choice', *Journal of Consumer Psychology*, 24(3), pp. 320–335. Available at: https://doi.org/10.1016/j.jcps.2014.01.002. [Accessed January 2025]

Ghaemi Kerahrodi, J. and Michal, M. (2020) 'The fear-defense system, emotions, and oxidative stress', *Redox Biology*, 37, p. 101588. Available at: https://doi.org/10.1016/j.redox.2020.101588. [Accessed February 2025]

Godos, J. *et al.* (2020) 'Diet and Mental Health: Review of the Recent Updates on Molecular Mechanisms', *Antioxidants*, 9(4), p. 346. Available at: https://doi.org/10.3390/antiox9040346. [Accessed February 2025]

Gupta, M. *et al.* (2021) 'Mood Based Food Recommendation System', in *2021 Asian Conference on Innovation in Technology (ASIANCON)*. IEEE, pp. 1–6. Available at: https://doi.org/10.1109/ASIANCON51346.2021.9545065. [Accessed February 2025]

Horovitz, O. (2025) 'Nutritional Psychology: Review the Interplay Between Nutrition and Mental Health', *Nutrition Reviews*, 83(3), pp. 562–576. Available at: https://doi.org/10.1093/nutrit/nuae158. [Accessed February 2025]

Jain, D.K., Shamsolmoali, P. and Sehdev, P. (2019) 'Extended deep neural network for facial emotion recognition', *Pattern Recognition Letters*, 120, pp. 69–74. Available at: https://doi.org/10.1016/j.patrec.2019.01.008. [Accessed January 2025]

Jang, E.-H. *et al.* (2015) 'Analysis of physiological signals for recognition of boredom, pain, and surprise emotions', *Journal of Physiological Anthropology*, 34(1), p. 25. Available at: https://doi.org/10.1186/s40101-015-0063-5. [Accessed February 2025]

Kitayama, S. and Park, J. (2017) 'Emotion and biological health: the socio-cultural moderation', *Current Opinion in Psychology*, 17, pp. 99–105. Available at: https://doi.org/10.1016/j.copsyc.2017.06.016. [Accessed February 2025]

Lakhan, S.E. and Vieira, K.F. (2008) 'Nutritional therapies for mental disorders', *Nutrition Journal*, 7(1), p. 2. Available at: https://doi.org/10.1186/1475-2891-7-2. [Accessed February 2025]

Martinez-Gorospe, A. *et al.* (2021) 'Food recommender system based on weighted ingredients, body mass index and allergies; using the Random Forest algorithm', in *2021 Mexican International Conference on Computer Science (ENC)*. IEEE, pp. 1–7. Available at: https://doi.org/10.1109/ENC53357.2021.9534806. [Accessed January 2025]

Murphy, S.P. and Barr, S.I. (2006) 'Recommended Dietary Allowances should be used to set Daily Values for nutrition labeling', *The American Journal of Clinical Nutrition*, 83(5), pp. 1223S-1227S. Available at: https://doi.org/10.1093/ajcn/83.5.1223S. [Accessed February 2025]

Muscaritoli, M. (2021) 'The Impact of Nutrients on Mental Health and Well-Being: Insights From the Literature', *Frontiers in Nutrition*, 8. Available at: https://doi.org/10.3389/fnut.2021.656290. [Accessed February 2025]

Owoyemi, E.P. *et al.* (2024) 'Nutritional Genomics: The Use of Personalized Diets for Managing Depression', *Journal of Complementary and Alternative Medical Research*, 25(11), pp. 23–37. Available at: https://doi.org/10.9734/jocamr/2024/v25i11581. [Accessed February 2025]

Schlechter, P. *et al.* (2023) 'The Short Mood and Feelings Questionnaire from adolescence to emerging adulthood: Measurement invariance across time and sex.', *Psychological Assessment*, 35(5), pp. 405–418. Available at: https://doi.org/10.1037/pas0001222. [Accessed January 2025]

'Scientific Opinion on the Tolerable Upper Intake Level of calcium' (2012) *EFSA Journal*, 10(7). Available at: https://doi.org/10.2903/j.efsa.2012.2814. [Accessed February 2025]

'Scientific Opinion on the Tolerable Upper Intake Level of vitamin D' (2012) *EFSA Journal*, 10(7). Available at: https://doi.org/10.2903/j.efsa.2012.2813. [Accessed February 2025]

Smith, T.W. *et al.* (2004) 'Hostility, Anger, Aggressiveness, and Coronary Heart Disease: An Interpersonal Perspective on Personality, Emotion, and Health', *Journal of Personality*, 72(6), pp. 1217–1270. Available at: https://doi.org/10.1111/j.1467-6494.2004.00296.x. [Accessed February 2025]

Steptoe, A. (2019) ‘Happiness and Health’, *Annual Review of Public Health*, 40(1), pp. 339–359. Available at: https://doi.org/10.1146/annurev-publhealth-040218-044150. [Accessed February 2025]

Tardy, A.-L. *et al.* (2020) ‘Vitamins and Minerals for Energy, Fatigue and Cognition: A Narrative Review of the Biochemical and Clinical Evidence’, *Nutrients*, 12(1), p. 228. Available at: https://doi.org/10.3390/nu12010228. [Accessed February 2025]

Tee, E.S. *et al.* (2023) ‘Review of recommended energy and nutrient intake values in Southeast Asian countries’, *Malaysian Journal of Nutrition*, 29(2). Available at: https://doi.org/10.31246/mjn-2023-29-2-rni-rda-sea-review. [Accessed February 2025]

Turck, D., Bohn, T., Castenmiller, J., de Henauw, S., Hirsch-Ernst, K., Knutsen, H.K., Maciuk, A., Mangelsdorf, I., McArdle, H.J., Pentieva, K., Siani, A., Thies, F., Tsabouri, S., Vinceti, M., Crous-Bou, M., *et al.* (2023) ‘Scientific opinion on the tolerable upper intake level for folate’, *EFSA Journal*, 21(11). Available at: https://doi.org/10.2903/j.efsa.2023.8353. [Accessed February 2025]

Turck, D., Bohn, T., Castenmiller, J., de Henauw, S., Hirsch-Ernst, K., Knutsen, H.K., Maciuk, A., Mangelsdorf, I., McArdle, H.J., Pentieva, K., Siani, A., Thies, F., Tsabouri, S., Vinceti, M., Bornhorst, J., *et al.* (2023) ‘Scientific opinion on the tolerable upper intake level for manganese’, *EFSA Journal*, 21(12). Available at: https://doi.org/10.2903/j.efsa.2023.8413. [Accessed February 2025]

Turck, D. *et al.* (2024) ‘Scientific opinion on the tolerable upper intake level for iron’, *EFSA Journal*, 22(6). Available at: https://doi.org/10.2903/j.efsa.2024.8819. [Accessed February 2025]

Vaishnavi, S. *et al.* (2024) ‘Nutrition Recommendation System for Sports Persons using Random Forest Algorithm’, in *2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC)*. IEEE, pp. 164–169. Available at: https://doi.org/10.1109/ICSSEECC61126.2024.10649420. [Accessed January 2025]

Vegesna, Dr.V. (2024) ‘AI-Driven Personalized Nutrition: A system for Tailored Dietary Recommendations’, *International Research Journal of Computer Science*, 11(07), pp. 545–550. Available at: https://doi.org/10.26562/irjcs.2024.v1107.02. [Accessed January 2025]

Yılmaz, C. and Gökmen, V. (2020) ‘Neuroactive compounds in foods: Occurrence, mechanism and potential health effects’, *Food Research International*, 128, p. 108744. Available at: https://doi.org/10.1016/j.foodres.2019.108744. [Accessed February 2025]

Young, L.M. *et al.* (2019) ‘A Systematic Review and Meta-Analysis of B Vitamin Supplementation on Depressive Symptoms, Anxiety, and Stress: Effects on Healthy and “At-

Risk" Individuals', *Nutrients*, 11(9), p. 2232. Available at: https://doi.org/10.3390/nu11092232. [Accessed February 2025]

Jubeile Mark Baladjay *et al*. (2023) 'Performance evaluation of random forest algorithm for automating classification of mathematics question items', *World Journal of Advanced Research and Reviews*, 18(2), pp. 034–043. Available at: https://doi.org/10.30574/wjarr.2023.18.2.0762. [Accessed February 2025]

APPENDIX

Appendix A – Monthly Project Timeline

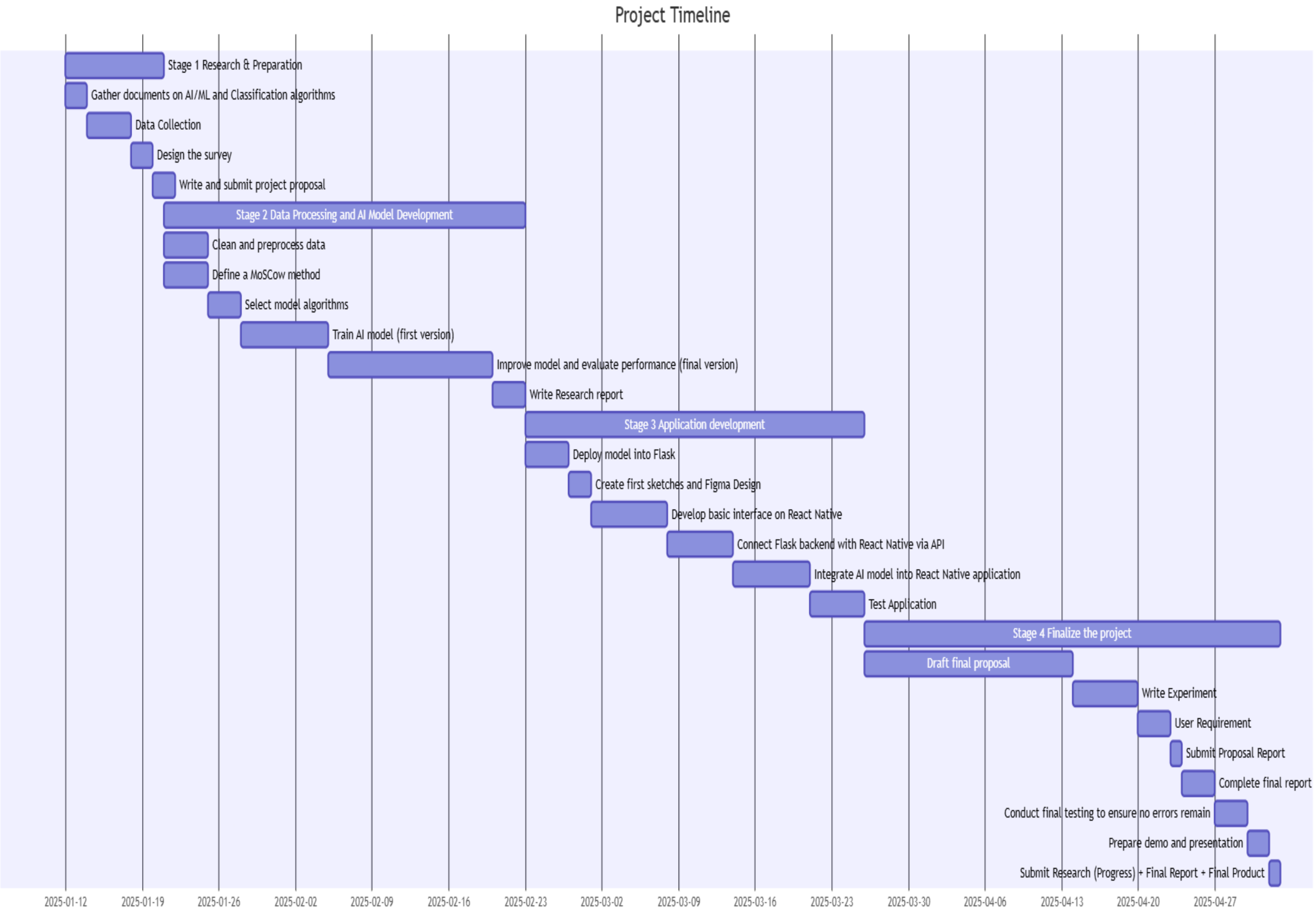
Month	Task Name	Start	End	Duration (days)
January	**Stage 1: Research & Preparation**	1/12/2025	1/20/2025	9
	Gather documents on AI/ML and Classification algorithms	1/12/2025	1/13/2025	2
	Data Collection	1/14/2025	1/17/2025	4
	Design the survey	1/18/2025	1/19/2025	2
	Write and submit project proposal	1/19/2025	1/20/2025	2
	Stage 2: Data Processing and AI Model Development	1/21/2025	2/22/2025	34
	Clean and preprocess data	1/21/2025	1/24/2025	4
	Define a MoSCow method	1/21/2025	1/24/2025	4
	Select model algorithms	1/25/2025	1/27/2025	3
	Train AI model (first version)	1/28/2025	2/4/2025	8

February	Improve model and evaluate performance (final version)	2/5/2025	2/19/2025	15
	Write Research report	2/20/2025	2/22/2025	3
	Stage 3: Application development	2/23/2025	3/25/2025	31
	Deploy model into Flask	2/23/2025	2/26/2025	4
	Create first sketches and Figma Design	2/27/2025	2/28/2025	2
March	Develop basic interface on React Native	3/1/2025	3/7/2025	7
	Connect Flask backend with React Native via API	3/8/2025	3/13/2025	6
	Integrate AI model into React Native application	3/14/2025	3/20/2025	7
	Test Application	3/21/2025	3/25/2025	5
	Stage 4: Finalize the project	3/26/2025	5/2/2025	38
	Draft final proposal	3/26/2025	4/13/2025	19
April	Write Experiment	4/14/2025	4/19/2025	20
	User Requirement	4/20/2025	4/22/2025	3

	Submit Proposal Report	4/23/2025	4/23/2025	1
	Complete final report	4/24/2025	4/26/2025	3
	Conduct final testing to ensure no errors remain	4/27/2025	4/29/2025	3
	Prepare demo and presentation	4/30/2025	5/1/2025	2
May	Submit Research (Progress) + Final Report + Final Product	5/2/2025	5/2/2025	1

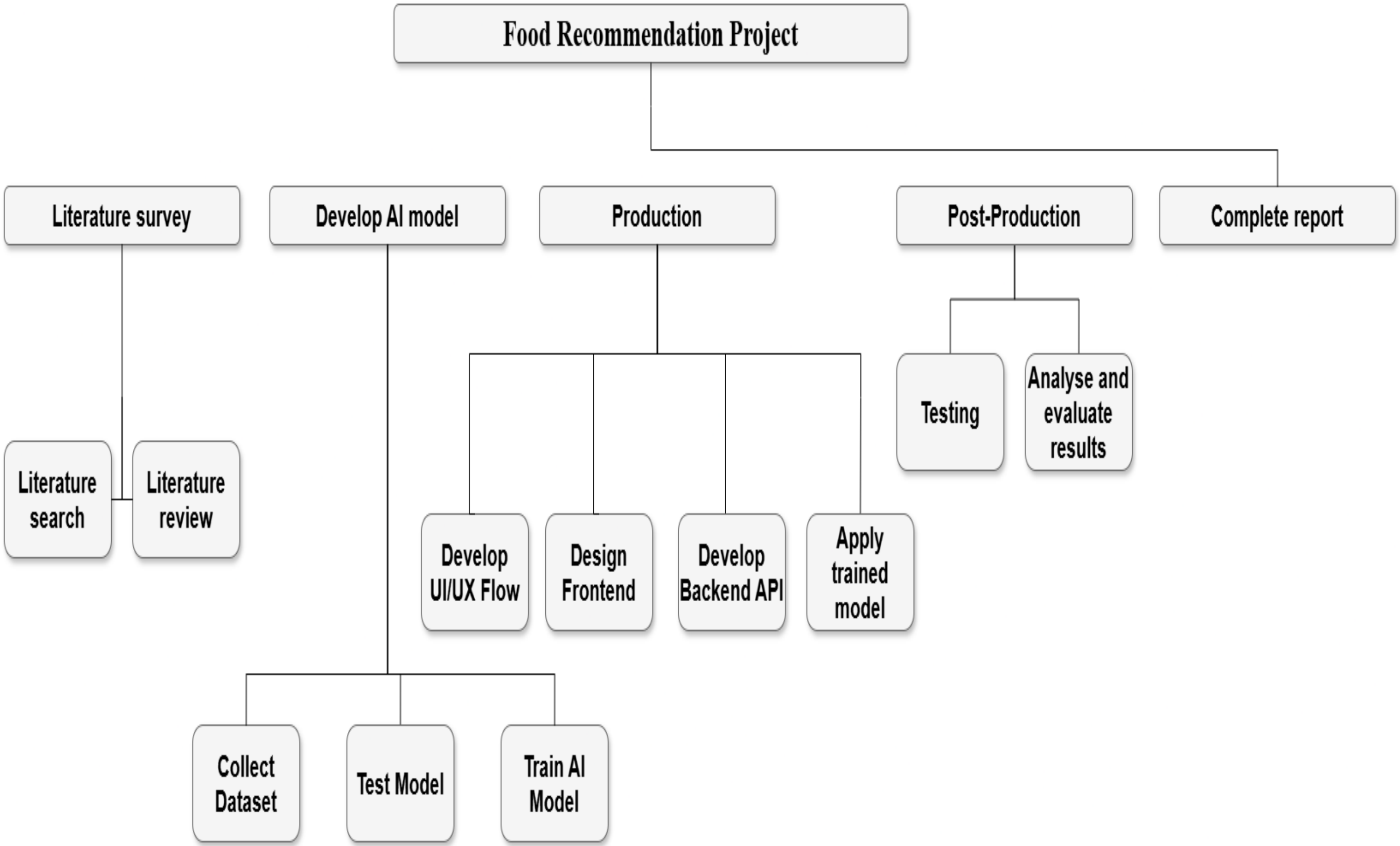
Appendix A. Monthly Project Timeline

Appendix B – Gantt Chart of Project Execution



Appendix B. Gantt Chart of Project Execution

Appendix C – Work Breakdown Structure (WBS)



Appendix C. Work Breakdown Structure (WBS)

Appendix D - List of priority nutrients in different moods table

Mood	Priority	Nutrient	Effectiveness	References
Sad	1	Polyunsaturated Fats	Reduces inflammation and improves depressive symptoms, especially EPA is shown effective in RCTs.	(Muscaritoli, 2021)
	2	Vitamin D	Enhances serotonin synthesis through gene activation (TPH2), supports emotional recovery.	(Owoyemi *et al*., 2024)
	3	Protein	Precursor to serotonin; when consumed with carbohydrates, increases serotonin availability in brain.	(Lakhan and Vieira, 2008)
	4	Vitamin B6	Cofactors in synthesis of serotonin and dopamine; supplementation reduces depressive symptoms.	(Young *et al*., 2019)
	5	Vitamin B12		
	6	Magnesium	Calms the nervous system, regulates GABA, and improves mood and sleep in depression.	(Muscaritoli, 2021)
	7	Zinc	Modulates NMDA receptors, reduces neuroinflammation, supports mood regulation and cognition.	(Horovitz, 2025)
Fear	1	Magnesium	Reduces stress and anxiety by regulating HPA axis and enhancing GABAergic activity.	(Muscaritoli, 2021)
	2	Polyunsaturated Fats	Decreases inflammation and cortisol; improves emotional resilience under chronic stress.	(Muscaritoli, 2021)
	3	Vitamin B6	Antioxidant; reduces oxidative stress and modulates cortisol and neurotransmitter synthesis.	(Young *et al*., 2019)
	4	Vitamin B12		
	5	Vitamin C	Improved symptoms in alcoholic men with latent scurvy	(Horovitz, 2025)
Neutral	1	Carbohydrates	Provides steady glucose to support brain energy and stable mood.	(Horovitz, 2025)
	2	Protein	Supplies amino acids needed for neurotransmitter synthesis.	(Lakhan and Vieira, 2008)
	3	Vitamin B1		(Tardy *et al*., 2020)

	4	Vitamin B2	Supports energy metabolism, brain cell function, and cognitive performance.	
	5	Vitamin B3		
	6	Vitamin B5		
	7	Vitamin B6		
	9	Vitamin B12		
	10	Magnesium	Oxygen transport, energy production Supports neurological function and energy metabolism	(Tardy *et al.*, 2020)
	11	Zinc		
	12	Iron	Supports oxygen delivery and enhances attention, memory, and cognitive function.	(Tardy *et al.*, 2020)
Happy	1	Protein	Provides tryptophan for as a precursor to serotonin; supports mood elevation when consumed with carbohydrates.	(Lakhan and Vieira, 2008)
	2	Carbohydrates	Boosts insulin, promotes tryptophan uptake in brain, thereby increasing serotonin synthesis.	(Horovitz, 2025)
	3	Vitamin D	Modulates serotonin production; associated with positive mood and emotional well-being.	(Owoyemi *et al.*, 2024)
	4	Polyunsaturated Fats	Regulates emotion, reduces cortisol, enhances mood stability and cognitive function.	(Muscaritoli, 2021)
	5	Magnesium	Regulates neurotransmitters; promotes calm, positive mood and reduces mild emotional imbalance.	(Muscaritoli, 2021)
Surprise	1	Carbohydrates	Provides immediate energy; enhances alertness and attention in response to novelty or stimulus.	(Horovitz, 2025)
	2	Vitamin B1	Supports energy metabolism and neurotransmitter synthesis under acute cognitive demand.	(Tardy *et al.*, 2020)
	3	Vitamin B2		
	4	Vitamin B3		
	5	Vitamin B5		
	6	Vitamin B6		
	7	Vitamin B12		

	8	Protein	Provides tyrosine as a precursor for dopamine and norepinephrine, enhancing cognitive speed and motivation.	(Horovitz, 2025)
	9	Vitamin C	Modulate neuroimmune function; contribute to mood regulation and acute cognitive response.	(Tardy *et al.*, 2020)
	10	Vitamin D		
Disgust	1	Dietary Fiber	Improves gut motility, binds toxins, restores digestive comfort after visceral or food-related disgust.	(Yılmaz and Gökmen, 2020)
	2	Magnesium	Calms visceral tension; may reduce nausea, gut reactivity and somatic response to aversive stimuli.	(Muscaritoli, 2021)
	3	Zinc	Supports mucosal healing, immune modulation, and gut-brain axis recovery after nausea/discomfort.	(Horovitz, 2025)
	4	Vitamin B6	Supports GABA synthesis; may alleviate visceral discomfort linked to disgust.	(Yılmaz and Gökmen, 2020)
Angry	1	Magnesium	Calms the nervous system via GABA regulation; reduces excitability and stress-induced aggression.	(Muscaritoli, 2021)
	2	Vitamin C	Reduces oxidative stress and cortisol; supports adrenal balance under emotional reactivity.	(Horovitz, 2025)

Appendix D. List of priority nutrients in different moods table

Appendix E – Recommended Daily Intake For each Nutrient table

Nutrient	Children (< 16 years)	Adults (>= 16 years)	Unit	
Caloric Value	1800	3300	kcal/day	(Tee *et al.*, 2023)
Fat	70000	128333.33	mg/day	(Godos *et al.*, 2020)
Polyunsaturated Fats	3000	3000	mg/day	(Godos *et al.*, 2020)
Carbohydrates	292500	536250	mg/day	(Tee *et al.*, 2023)
Sugars	45000	82500	mg/day	(Tee *et al.*, 2023)

Protein	27000	71000	mg/day	(Tee *et al.*, 2023)
Dietary Fiber	13000	30000	mg/day	(Tee *et al.*, 2023)
Sodium	1500	2000	mg/day	(Tee *et al.*, 2023)
Vitamin A	900	3000	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)
Vitamin B1	0.7	1.4	mg/day	(Tee *et al.*, 2023)
Vitamin B11	0.4	1	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023; Turck, Bohn, Castenmiller, de Henauw, Hirsch-Ernst, Knutsen, Maciuk, Mangelsdorf, McArdle, Pentieva, Siani, Thies, Tsabouri, Vinceti, Crous-Bou, *et al.*, 2023)
Vitamin B12	0.0015	0.003	mg/day	(Tee *et al.*, 2023)
Vitamin B2	0.7	1.7	mg/day	(Tee *et al.*, 2023)
Vitamin B3	12	16	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)
Vitamin B5	4	5	mg/day	(Tee *et al.*, 2023)
Vitamin B6	0.9	1.7	mg/day	(Tee *et al.*, 2023)
Vitamin C	50	100	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)
Vitamin D	0.015	0.015	mg/day	('Scientific Opinion on the Tolerable Upper Intake Level of vitamin D', 2012; Tee *et al.*, 2023)
Vitamin E	7	15	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)
Vitamin K	0.06	0.12	mg/day	(Tee *et al.*, 2023)
Calcium	1000	2500	mg/day	('Scientific Opinion on the Tolerable Upper Intake Level of calcium', 2012; Tee *et al.*, 2023)
Copper	0.7	0.9	mg/day	(Tee *et al.*, 2023)
Iron	10	18	mg/day	(Tee *et al.*, 2023; Turck *et al.*, 2024)
Magnesium	200	420	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)
Manganese	1.5	2.3	mg/day	(Tee *et al.*, 2023; Turck, Bohn, Castenmiller, de Henauw, Hirsch-Ernst, Knutsen, Maciuk, Mangelsdorf, McArdle, Pentieva, Siani, Thies, Tsabouri, Vinceti, Bornhorst, *et al.*, 2023)

Phosphorus	800	1250	mg/day	(Tee *et al.*, 2023)
Potassium	2600	4700	mg/day	(Tee *et al.*, 2023)
Zinc	12	40	mg/day	(Murphy and Barr, 2006; Tee *et al.*, 2023)

Appendix E. Recommended Daily Intake For each Nutrient table