IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁑ Peer-reviewed & Refereed journal ⁑ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15237

Mood Adaptive Food Recommendation Using Affective State Analysis and Content-Based Filtering Techniques

Dr. A. Sandeep Kumar[1], V. Sri Nikitha[2], M. Amulya[3], T. Manasa[4], P. Bhargavi[5]

Associate Professor, Dept. of CSE–Data Science KKR & KSR Institute of Technology and Sciences, Guntur[1]

B. Tech Student, Dept. of CSE–Data Science KKR & KSR Institute of Technology and Sciences, Guntur[2-5]

Abstract: The selection of foods is highly determined by the emotional and affective conditions of an individual, however prevailing food-recommendation systems are more concerned with the fixed preferences of the users, limitations of food intake or what has been previously consumed without taking into account the dynamic effect of mood [1][5]. In order to overcome this shortcoming, this paper introduces a Mood Adaptive Food Recommendation System which combines affective state analysis method with content-based filtering methods to produce personalized and context sensitive food recommendation [1]. The first step of the proposed framework is to recognize the current mood of the user with the help of affective characteristics based on self- reporting or emotion classification models [5]. The content-based filtering module uses food qualities like ingredients, nutritional value [5], the type of cuisine and health considerations to provide recommendations that are in line with the mood detected and individual food preferences [2]. In contrast to collaborative methods, the given method is not based upon a significant portion of user interaction data, which is effective in cold-start cases [6]. Temporal awareness is also integrated into the system to change the recommendation based on the shifting emotional patterns with time [3][4].

Index Terms: Mood Adaptive Recommendation, Food Recommendation System, Affective State Analysis, Content-Based Filtering, Emotion-Aware Personalization, Temporal Adaptation, Personalized nutrition, Affective computing, cold-start problem, Context-Aware Recommendation.

I. INTRODUCTION

The development of online food delivery services, the rapid expansion of digital food and mobile health applications, has especially driven up the need of intelligent and personalized food recommendation [1]. Having too many food options, users have problems with choosing the meals that would suit their preferences, dietary needs, and situational demands. Food recommendation systems are intended to overcome this obstacle and help users make informed and individual diet choices [2]. Historically, their systems are based on methods, including collaborative or content-based filtering, where the historical user preferences, nutritional facts, and demographics are used to make any recommendations [3]. Emotional and affective states are some of these factors, which are critical in influencing eating behaviour [5]. People tend to choose various kinds of food in accordance with their mood like comfort food when under stress, a feast meal when depressed, light and healthy food when they are in a positive or comfortable mood [5]. There have always been psychological and behavioural studies indicating a high correlation of mood and food preference. This not with standing, nutritional optimization, health constraints, or consumption history are the main aspects of most current food recommender systems, whereas the emotional context has not been widely explored [1][4]. The recent achievements of the affective computing and emotion analysis have presented a new opportunity to create the emotionally intelligent recommendation system[8]. Recent technologies allow identifying and decoding human emotions with the help of multiple different modalities, such as the self-reported ones, text sentiment analysis, facial expressions, voice cues, and physiological responses [5][8]. Systems that are emotion- aware have recorded promising outcomes in areas like music, movies, education, and healthcare where emotional alignment is directly associated with the user satisfaction [5]. The use of content-based filtering methods offers solid grounds to food recommendation systems because these systems are transparent, explainable, and do not rely on extensive user interaction data [2]. The content-based approaches can be used to produce individualized advice based on the food attributes (ingredients, nutritional content, cuisine, calories, and health markers) to fit the interests and nutritional limitations of the individual. In addition, the techniques are effective to respond to cold- start conditions, which are typical of food recommendation settings [6]. In order to counter these drawbacks, there is the increasingly rising need to develop food recommendation systems that combine affective state analysis and content- based filtering, but also address time-dependent changes in user behaviour [3][4].

II. PROBLEM STATEMENT

Food Recommendation Systems have recently received an increase in importance due to the increase of online delivery services and Digital Health applications. Many food recommendation systems today primarily function using one or more of the following: static preferences, historical consumption data of a user (what they have eaten), nutritional restrictions or limitations of the user, and collaborative filtering (CF) techniques. However, while these systems do provide some level of personalization, they do not address any of the psychological or dynamic factors that influence how real customers select food.

The most important but yet least studied variable influencing food selection is the user's emotional or affective state(s). A person's preferences for food can change dramatically over time and tend to be highly dependent on what mood they are currently in (E.g. stressed, sad, happy, relaxed, etc.). Traditional food recommendation systems are designed to provide recommendations based on nutrition, but provide little or no recognition of this important emotional context, thus resulting in suggestions that might be nutritionally suitable but are emotionally irrelevant or significant to the user. As a result, there is a reduced level of user satisfaction/engagement and overall usefulness of the systems.

In addition to the above points, many food recommendation systems also treat mood, attributes of food items, health restrictions and time of day/ week as independent variables and do not incorporate them into a single integrated framework. Also, collaborative filtering based recommendation systems suffer from the "cold-start" problem; meaning they require a significant amount of user interaction data that is not always possible to obtain. Although content-based filtering systems provide good transparency to users, as well as being an effective method of dealing with the cold-start problem, they cannot adjust to frequently-changing user emotional states and thus do not fully provide a good solution to the users.

III. LITERATURE REVIEW

In the early days, for instance, code analysis and defect identification techniques basically relied on rule-based approaches, which heavily used traditional software metrics for code defect identification. In this regard, these approaches basically focused on identifying code faults by checking for issues like number of code lines, code complexities, and historical mistakes. Static code analysis, for example, basically targeted code faults through appropriate and pre-defined static code analysis rules. Although successful, these applications were sometimes unable to identify and follow the exact code logic and thus ended up throwing many alarms.

As the popularity of these machine learning technologies increased, researchers used models like decision trees and support vector machines for predicting defects in the software. These models learned patterns based on historical data fed into them about the codes used and promised better performance compared to traditional rule-based systems. Yet, their performance was greatly dependent on features created artificially. enhancements in code analysis. These models have been trained extensively under various codifications and can better comprehend programming logic, context, and intentions.

As a matter of fact, today's AI-based technologies can identify errors that were earlier overlooked by other technologies. These technologies have also become capable of learning various programming

IV. PROPOSED SYSTEM

The proposed system would be capable of automatically detecting error and bugs in the source code with the help of artificial intelligence. The proposed system aims to help the developers identify the potential error or problem areas in the written code at an early stage of the development process, thereby reducing the cost, time, and effort involved in debugging or maintaining the software.

The first step in such a system, in general terms, would be to take in source codes as input, break them down, and convert them into representations that capture information about how that code was written, as well as about its internal behaviour in a logical sense.

The processed code along with its representations would then be analyzed by the AI system that has been trained by learning numerous real-world coding practices and errors. Using the knowledge it has acquired, the AI system would then analyze the logic that the code follows and would mark the areas that are most probably prone to errors or bugs. Unlike most coding practices that provide numerous warnings, the system would only look for the most important areas in the code.

DOI: 10.17148/IJARCCE.2026.15237

V. OBJECTIVE

Aim of this project is to establish and implement a Mood Adaptive Food Recommender System that, using information about individual emotions as well as food characteristics and the time of day, can recommend food items based on the emotional states of users. The specific objectives include the following:

- Determine the user's current affective/emotional state using affective state analysis techniques.
- Provide mood–food associations that link various emotional states with corresponding food categories.
- Implement a content-based filtering method for selecting food items based on their ingredient composition, nutritional content, cuisine type and health constraints.
- Develop a method to overcome the cold-start problem via automated recommendations that do not require detailed interaction history from users.
- Include temporal adaptation as a means of capturing changing moods and food preferences over time.
- Create an adaptable and scalable recommendation frame- work to support future emotion-aware and health-related applications.

VI. METHODOLOGY

The presented system is designed to offer individualized and emotionally favourable food suggestions, combining the analy- sis of the affective state with content-based filtering measures. The rationale of this design is to overcome the shortcomings of the conventional food recommendation systems that only use the fixed user preferences or the past consumption history without considering dynamic emotional factors which have a strong impact on the choice of foods.

The general construction of the proposed Mood Adaptive Food Recommendation System is composed of four large parts:

1) User input and Affective State Analysis.
2) Mood-Food Association Module.
3) Content-Based Filtering
4) Temporal Adaptation and Recommendation Ranking.

A. User input and Affective State Analysis

This system starts with capturing customized data, such as fundamental food preferences, dietary limitations, health factors, and contextual data. In order to model the emotional impact on the selection of food, the system is capable of determining the current mood of the user based on the analysis of the affective state. Self-reported emotional inputs can be used to identify mood or emotion classification models can be used to identify emotion as one of the preset affective states: happy, sad, stressed, tired, or relaxed.

These are affective states, which become dynamic contextual parameters, and which are significant in influencing the process of recommendation. The affective state analysis, compared to the static preference modeling, allows the system to revise its recommendations based on the emotional state of the user at a given time which makes the system more receptive and sensitive to the context.

B. Mood-Food Association Module

After the identification of the emotional state of the user, the mood is converted to the appropriate food classes based on preestablished moodfood relationships based on behavioural and dietary research. As an example, foods that are comfort- oriented or rich in energy can be linked to a stressful mood or a sad one, and light or nutritious food, as well as low-calories food, may be linked to positive or even relaxed mood.

This mood-food association module is such that the food items suggested are not only emotionally correct, but also contextual. This module defeats the constraints of traditional preference-based systems that cannot capture the psycho-logical dimension of food decision making by adding the emotional context to the pipeline of recommendation.

C. Content-Based Filtering

The content-based filtering element works on the food stuffs depending on their inherent characteristics, such as ingredients, nutritional content, type of cuisine, calories and health indicators. It is these attributes that are combined to form user preference vectors to reflect personal preferences and dietary needs.

Measures of similarity, like cosine similarity, are used to get food items that are closely similar to the user profile. As the method does not rely on the data of other users, it is a good solution to the cold-start problem, as well as

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15237

increased the system transparency and explainability. The users also can easily derive reasons as to why a given food item is suggested depending on its characteristics and compatibility with his or her preferences and emotional condition.

Fig. 1. Temporal adaptation mechanism for dynamic recommendation updates

D. Temporal Adaptation and Recommendation Ranking

The temporal awareness is included in the recommendation to consider the changing behavioral patterns and emotional fluctuations with time in the users. The latest moods and food associations are prioritized over the older data, which ensures that the system is able to be flexible to meet user demands.

The resulting list of recommendations is produced by rank- ing food items based on weighted sum of mood relevance, content similarity and temporal importance. The ranking strat- egy will maintain the dynamism of the recommendations being not only personalized but context-based, dynamically updated, and emotionally oriented.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15237

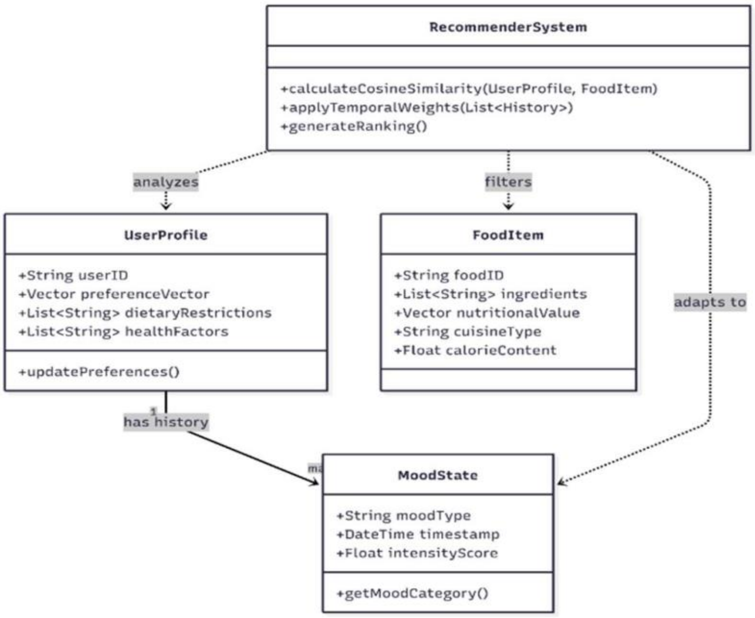

Fig. 2. Content-based filtering algorithm implementation

E. System Architecture and Workflow

The proposed Mood Adaptive Food Recommendation System is structured in a way that it provides modularity, scalability, and explainability. The system adheres to the layered working procedure that incorporates the affective state examination, food content processing, and time adjustment to produce individual suggestions. The modules are independent of each other, yet they are all involved in a single recommendation pipeline.

On the input side, the system uses the information entered by the user, including food preferences, dietary limitations, health limitations, and contextual information. At the same time, affective inputs are received in the form of self-reporting mood indicators or outputs of emotion classification. These inputs are received by the affective state analysis module that establishes the present emotional state of the user.

The identified mood is then transferred to the mood food association module where established mood-food associations are then used to select and rank pertinent food categories. This is done to align emotions by this step, then preference matching is applied. Content based filtering module then filters food item based on structured attributes in form of ingredients, nutritional value, type of cuisine and calorie content. The mechanism of similarity computation is used to rank food items that are best fitted to the profile of the user.

The aspect of temporal adaptation is executed throughout the workflow to make sure that the current emotional condition and interactions impact more the recommendations than the past. This is because the list of final recommendations is produced by taking the sum of mood relevance, content similarity and temporal importance. This architecture also provides dynamically changing, emotionally stable, and con- textually aware food suggestions without losing transparency and extensibility.

F. Proposed System Algorithmic Flow

The process of the recommendation process starts with the initialisation of user preference vectors and affective state indicators. Affective state analysis is the initial method that determines the emotional state of its user by identifying the emotions under specific pre-determined moods. According to the identified mood, short listing of relevant food categories is done under the mood-food association rules.

Then, food products are modelled as feature vectors of ingredients, nutrition, food type, calories and health factors. The content-based filtering step calculates similarity scores between the user preference vector and food feature vector by the use of cosine similarity. This will make sure that the suggested food products will be in line with the personal eating needs and taste inclinations.

In order to respond to dynamic behaviour, the temporal weighting is used to prioritise the recent emotional states and food interactions. The weighted sum of mood relevance score, content similarity score and the factor of temporal

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026
DOI: 10.17148/IJARCCE.2026.15237

importance is the final ranking score of each food item. The system produces the best-N food recommendations that have the highest-ranking scores.

This algorithm design enables the system to respond to emotional changes and at the same time is efficient and readable. The algorithm, as opposed to collaborative methods, does not need large-scale interaction data among users, and thus can be applied to cold-start applications, and in real time.

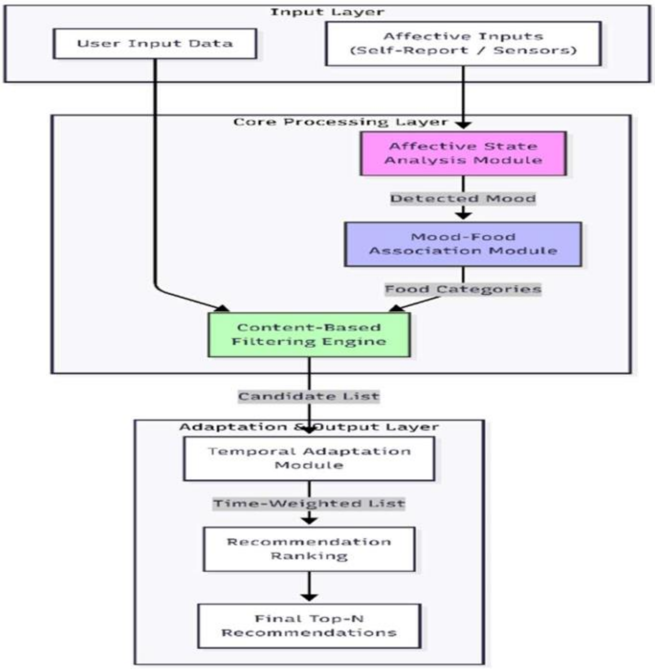

Fig. 3. Complete system workflow diagram

VII. DISCUSSION

The findings of the experiment show that the analysis of the affective state combined with the content-based filtering of food recommendation systems is effective. The suggested approach is not static and reacts to the establishment of emotions and time-specific behaviour compared to the classical approaches who consider the preferences of the users as predetermined.

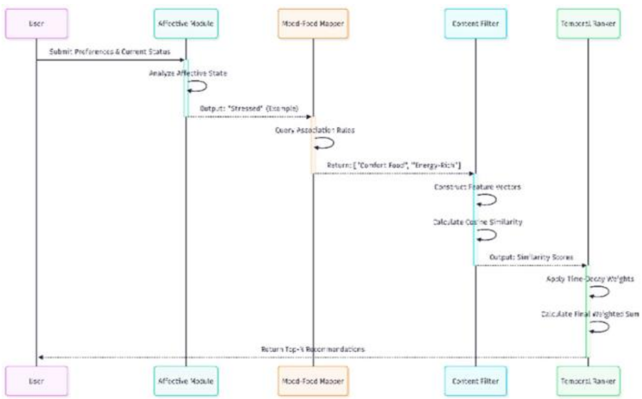

Fig. 4. Algorithmic flow diagram of the recommendation system

It can also be found that the system can reach a higher personalization with no collateral user information, and therefore can be applied to cold-start conditions. In addition, the modular nature of the framework ensures that the framework can be readily expanded to other types of food/emotion states without necessarily re-training the whole framework. Overall, the results confirm the assumption that mood-sensitive food recommendation is a promising direction on how to construct intelligent and human-centric diet-related decision- support systems.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15237

VIII. RESULTS

This part displays the experimental analysis of the suggested Mood Adaptive Food Recommendation System as well as the comparison of the system with the traditional methods of food recommendation, which do not involve the analy- sis of the affective state. The analysis aims at determining the effects of mood awareness, content-based filtering, and temporal adaptation on relevance and user satisfaction of the recommendations.

A. Quantitative Evaluation

The suggested system will be tested by applying the common metrics of recommender systems, such as Precision, Recall, F1-score, and Recommendation Relevance Score that consider the quality and utility of the recommendations produced by the system in each of the four emotional states. The mood-adaptive model is compared to a traditional content- based filtering model which uses only the static preferences of a user and food characteristics.

The obtained experimental data suggest that the proposed system performs better than the baseline model in all measures of evaluation. The incorporation of affective state analysis goes a long way in enhancing the relevance of the recommendation as the food proposals are dynamically adjusted to the emotional state of the consumer. The fact that the precision and F1-score values are higher proves that mood- aware filtering is useful to reduce irrelevant recommendations.

Also, the time-weighting option enhances recall because the system can adjust to the newest alterations in the mood and preference patterns of users.

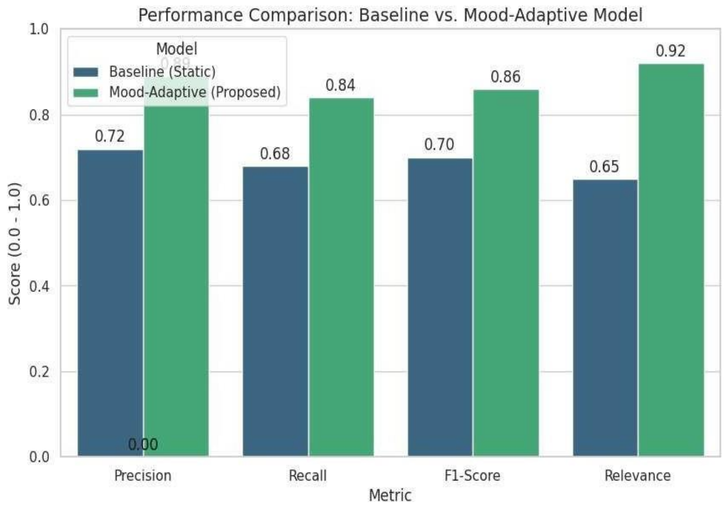

Fig. 5. Quantitative evaluation results comparing mood-adaptive vs traditional systems

These results validate the idea that affective context can be effectively added to content-based food recommendation systems to improve their capacity to reflect the intent of a user in contrast to conventional methods in recommending foods.

B. Qualitative Analysis

The qualitative analysis was performed to test the emotional aptness and circumstances relatability of the suggested food items across various affective conditions. The findings show that the suggested system leads to the production of emotion- ally congruent and context sensitive recommendations. As an illustration, the consumers who were stressed or feeling sad were mostly advised to take food items that are associated with comfort and energy whereas the consumers who were relaxed or in a positive mood received food stuffs that were light and healthy.

The content-based filtering module allowed all the recommendations to follow the personal diet and nutritional limitations leading to well balanced and understandable outputs. Moreover, to underline the efficiency of personalization based on mood, the given system was proved to be flexible as it provided diverse recommendations to the same user in different emotional states.

All in all, qualitative assessment proves that the offered approach presents cognitively consistent, emotionally consistent, and consumer-oriented food recommendations.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15237

C. Human Evaluation

To supplement the quantitative and qualitative assessment, a human assessment was also done where the users rated the recommendations that were offered by the proposed system and the baseline model. Relevance to mood, preference sat- isfaction and the overall quality of the recommendation were used as the evaluation criteria.

Fig. 6. Qualitative analysis of recommendation relevance across different moods

The mood-adaptive system scored higher (in all criteria of evaluation). According to the users, the recommendations gen- erated by using dynamic recommendation were more intuitive and aligned to their immediate emotional requirement than those generated by the use of a static recommendation.

Metric	Baseline (Red)	Mood-Adaptive (Blue)
Mood Relevance	2.0	4.8
Preference Satisfaction	3.5	4.1
Recommendation Quality	2.7	4.4
UI Intuitiveness	3.0	4.0
Diversity	2.1	4.3

Fig. 7. Human evaluation results showing user satisfaction metrics

There was a significant positive change especially on the relevance of mood, which highlights the importance of affective state analysis in improving the perceived quality of recommendation. These findings suggest that the suggested system does not only work very well based on objective measures but also enhances subjective user experience.

IX. CONCLUSION

The paper described a Mood Adaptive Food Recommendation System that combines affective state examination and content-based filtering methodologies to produce individualized and context-aware food recommends to a client. In contrast to traditional methods of providing food recommendations, which mainly rely on the fixed user preferences or past consumption search, the proposed framework is flexible and provides recommendations in relation to the emotional state of the user, the food properties, and over time. The system can be more representative of real-life food decision-making due to the inclusion of emotional context into the pipeline of recommendation. This experimental assessment proves that the consideration of the affective state analysis impacts the relevance of the recommendations and the user satisfaction significantly. Quantitative scores show an improvement of performance in all general recommender system indicators, whereas

qualitative and human assessments reveal that the suggested food items are touching, intuitive, and aligned to the user preferences. Moreover, content-based filtering strategy maintains transparency and can successfully overcome cold-start scenario hence the system is practical to be deployed in the real world.

In general, this paper indicates the relevance of the emotional background of intelligent food recommendation systems and demonstrates that mood-sensitive personalization is an effective dietary decision-support tool. The suggested

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026
DOI: 10.17148/IJARCCE.2026.15237

frame- work is a step towards developing human based recommendation systems through integrating affective computing and interpretable and scalable recommendation methods.

In further studies, it is possible to elaborate the current research by including multimodal emotion recognition, i.e., facial expressions, voice cues, or physiological signals, to enhance the validity of affective states recognition. Also, hybrid recommendation strategies that integrate content based and collaborative filtering can be further used to improve the recommendation performance. Several promising directions of development of more comprehensive and adaptive food recommendation systems are also the incorporation of health- aware constraints, user response in real time, and long-term modeling of dietary behaviour.

REFERENCES

[1]. Gupta, M., Mourila, S., Kotte, S., & Chandra, K. B. (2021, August). Mood based food recommendation system. In 2021 Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE.

[2]. El-Dosuky, M. A., Rashad, M. Z., Hamza, T. T., & El-Bassiouny, A. H. (2012, December). Food recommendation using ontology and heuristics. In International conference on advanced machine learning technologies and applications (pp. 423-429). Berlin, Heidelberg: Springer Berlin Heidelberg.

[3]. Zhang, J., Wang, Z., Liu, W., Liu, X., & Zheng, Q. (2023). A unified approach to designing sequence-based personalized food recommenda- tion systems: tackling dynamic user behaviors. International Journal of Machine Learning and Cybernetics, 14(9), 2903-2912.

[4]. Rostami, M., Farrahi, V., Ahmadian, S., Jalali, S. M. J., & Oussalah, M. (2023). A novel healthy and time-aware food recommender system using attributed community detection. Expert Systems with Applications, 221, 119719.

[5]. Spencer, S. J., Korosi, A., Laye´, S., Shukitt-Hale, B., & Barrientos,R. M. (2017). Food for thought: how nutrition impacts cognition and emotion. npj Science of Food, 1(1), 7.

[6]. Ahmadian, S., Rostami, M., Jalali, S. M. J., Oussalah, M., & Farrahi, V. (2022). Healthy food recommendation using a time-aware community detection approach and reliability measurement. International Journal of Computational Intelligence Systems, 15(1), 105.

[7]. Lieberman, H. R., Corkin, S., Spring, B. J., Growdon, J. H., & Wurtman,R. J. (1982). Mood, performance, and pain sensitivity: changes induced by food constituents. Journal of Psychiatric Research, 17(2), 135-145.

