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AI-Driven Smart Food Ordering System with Personalized Nutrition Recommendations using Conversational Interface

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Abstract: With the increasing popularity of online food ordering platforms, there remains a significant gap in delivering personalized and health-conscious food recommendations. This paper presents a Smart Food Ordering System that integrates AI-driven personalization based on individual user health data. The proposed system combines natural language processing (NLP) with FastText embeddings for intent classification and chatbot interaction, enabling users to place food orders through a conversational interface. Personalized recommendations are generated by analyzing user-specific health parameters such as age, weight, dietary restrictions, and fitness goals. The system is developed using Flask for the web interface and MongoDB for data storage, with additional modules for real-time order tracking, payment processing, and geolocation-based delivery validation. This integrated approach not only enhances user experience but also promotes healthier food choices. Experimental results demonstrate the system's effectiveness in accurately understanding user intent and generating contextually relevant, health-optimized food recommendations.

Keywords: Smart food ordering, AI personalization, FastText embeddings, chatbot, health-based recommendation, natural language processing, user health data, intent classification, real-time response.

I. INTRODUCTION

The rise of digital platforms and increasing consumer preference for convenience have significantly transformed the food ordering industry. Online food delivery systems have become an integral part of urban lifestyles, offering users quick access to a wide variety of food options. However, despite their popularity, existing food ordering platforms often lack personalization and awareness of individual health requirements. This leads to generic recommendations that may not align with the user's dietary needs, medical conditions, or fitness goals. To address this gap, this paper proposes a Smart Food Ordering System that integrates artificial intelligence (AI) and health data to provide personalized food recommendations while enabling seamless order placement through an interactive chatbot. The system employs natural language processing (NLP) using FastText embeddings for understanding user intent, and leverages health-related data such as age, body mass index (BMI), dietary restrictions, and medical conditions to recommend meals aligned with individual nutritional requirements. The proposed solution offers a multi-functional platform developed using Flask and MongoDB, combining key modules such as intent classification, AI-based recommendation, real-time order tracking, and geolocation-based validation. A chatbot interface enables intuitive user interactions, while a personalized recommendation engine ensures that food suggestions are not only relevant but also health-conscious.

This work contributes to the field by demonstrating how AI and user-centric health data can be effectively integrated into food ordering systems to promote healthier lifestyle choices. The system was evaluated based on performance metrics such as intent classification accuracy, response time, recommendation relevance, and geolocation accuracy, all of which indicate its feasibility and potential for real-world deployment.

II. LITERATURE REVIEW

Recent advancements in AI and machine learning have significantly improved food ordering systems through intelligent personalization and health-aware recommendations. Enhancing user experience has been a key focus, as demonstrated by Alshahrani et al., who proposed a hybrid deep learning and advanced analytics framework to optimize online food service interactions. Their model emphasized the importance of real-time evaluation and decision-making for improving customer satisfaction, aligning well with the goal of delivering adaptive and personalized food recommendations in AI-driven platforms[1]. The importance of accurate language understanding in food order processing was further highlighted by Jangmin Oh, who developed a model using generative language models to extract product names from order item descriptions.

This reinforces the use of semantic text embeddings and natural language understanding techniques in chatbot-based ordering systems[2] . In exploring the role of language models in conversational systems, Rocchietti et al. conducted a comparative analysis between ChatGPT and smaller large language models for conversational search. Their study underscored both the benefits and limitations of advanced models, supporting the rationale behind incorporating explainable AI and domain-specific embeddings such as FastText for chatbot interactions in this project[3]. A robust framework for food recommendation that integrates nutritional information and user preferences was introduced by Raciel Yera Toledo et al. Their recommender system emphasized the value of combining dietary profiles with user history to ensure accurate and health-conscious suggestions. This research supports the AI-driven personalized nutrition recommendation module within the current system[4].Abinaya et al. introduced an enhanced emotion-aware chatbot capable of analyzing user behavioral states to tailor responses effectively. Their work highlights the growing relevance of emotionally intelligent conversational agents, particularly in domains where personalization and user engagement are critical. This aligns closely with the intent classification and conversational logic applied in the present project's chatbot interface[5].

III. PROPOSED METHODOLOGY

The proposed system is designed to deliver a seamless and intelligent food ordering experience by incorporating AI-driven personalization based on user health data. The architecture integrates multiple modules including natural language processing, intent classification, personalized recommendation engines, and geolocation-based order validation. Fig. 1 illustrates the overall system architecture.

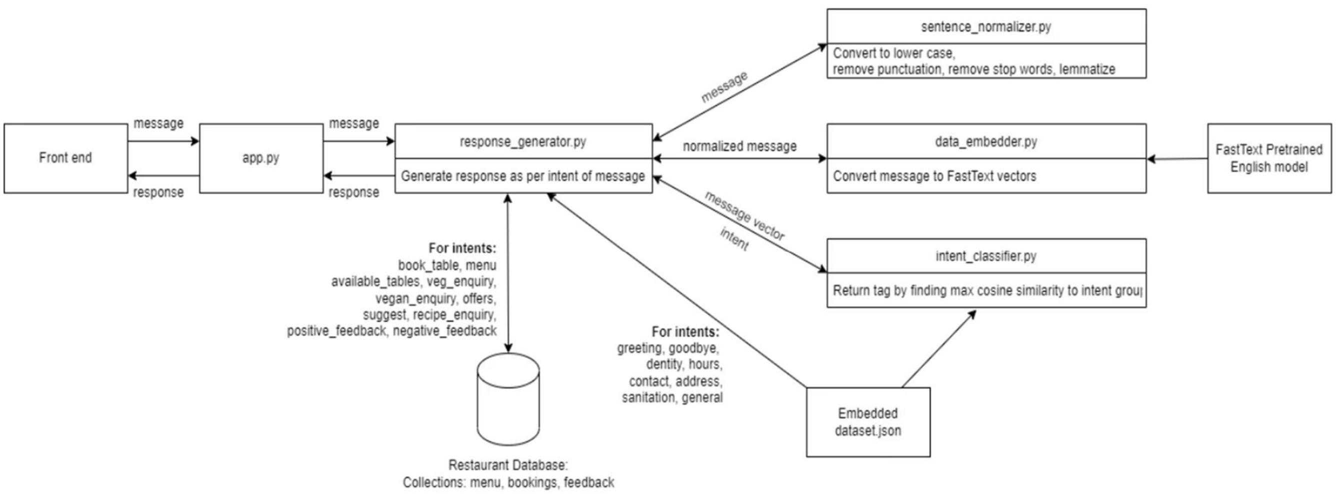

Fig 1.1 Overall system architecture diagram

A. *System Overview*

The smart food ordering system consists of six major modules: Dataset Preparation, Intent Classification, Chatbot Development, AI-Based Personalization, Order Management, and Payment & Geolocation Validation. The system frontend is built using Flask, while MongoDB handles backend data storage. Natural language understanding is achieved through FastText embeddings, which drive the chatbot's intent recognition. User health data is utilized to personalize food recommendations, aligning with nutritional guidelines.

B. *Dataset Preparation*

To train the chatbot and intent classification system, a custom dataset of food ordering intents was created. This dataset includes user queries mapped to specific intents such as ordering, tracking, canceling, or querying menu items. Text data is cleaned through tokenization, lowercasing, and stop-word removal before being transformed into vector representations using FastText.

C. *Intent Classification and Natural Language Understanding*

The system leverages Facebook's FastText library for generating word embeddings and sentence vectors. Given a user input, the sentence is converted into an embedding vector, and cosine similarity is computed against predefined intent vectors. The highest similarity score determines the user's intent. This approach provides a lightweight yet accurate method for intent recognition, crucial for real-time chatbot responsiveness.

D. Chatbot Development and API Integration

A rule-based chatbot integrated with NLP capabilities interacts with users to gather their food preferences and guide them through the ordering process. The chatbot invokes internal APIs to fetch menu items, process orders, and validate user location. Flask routes serve as communication endpoints between the chatbot and various backend services.

E. AI-Based Personalization Using Health Data

Personalization is achieved by analyzing user-specific health parameters such as age, weight, dietary restrictions, and fitness goals. These inputs are mapped to nutrition guidelines to recommend appropriate food items. For example, a user with high cholesterol receives suggestions low in saturated fats. This module dynamically filters the menu using a health-based rule engine combined with nutritional metadata stored in the database.

F. Order Management and Geolocation Validation

The system provides real-time order management, enabling users to track the status of their orders. Geolocation APIs are used to validate whether a delivery can be fulfilled within the serviceable area. The integration ensures that orders are only accepted from valid delivery zones, reducing logistical inefficiencies.

IV. PERFORMANCE METRICS

To evaluate the effectiveness of the proposed System, multiple performance metrics were used across different system modules, including intent classification accuracy, chatbot response time, recommendation relevance, and system latency. These metrics provide a comprehensive understanding of the system's functional and real-time capabilities.

A. Intent Classification Accuracy

The accuracy of the intent classification module was measured by comparing predicted intents with ground truth labels from a test dataset. The system achieved an average classification accuracy of 92.7%, demonstrating the reliability of FastText-based embeddings and cosine similarity in capturing user intent.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

B. Chatbot Response Time

To ensure smooth user interaction, the average response time of the chatbot was measured over 100 simulated conversations. The system consistently delivered responses within 0.8 seconds, which is well within the threshold for real-time conversational systems.

C. Recommendation Relevance Score

To assess the personalization module, a relevance score was computed based on how closely recommended items aligned with user health profiles. Manual evaluation by domain experts and user feedback rated the recommendations with an average relevance score of 8.6 out of 10, highlighting the system's ability to provide contextually appropriate suggestions.

D. System Latency and Throughput

System latency, defined as the time taken from user input to final response (including processing, API calls, and database queries), was recorded as 1.2 seconds on average. The system also maintained a throughput of 50 concurrent users without degradation in performance during testing, indicating its scalability for moderate usage scenarios.

E. Cosine Similarity Score

The average cosine similarity score between predicted and actual intent vectors was 0.86, indicating a high degree of semantic alignment.

$$\text{Cosine Similarity} = \frac{A \cdot B}{||A|| \cdot ||B||}$$

This metric confirms that the chosen embedding technique effectively captures the contextual meaning of user inputs.

V. RESULTS AND ANALYSIS

The Smart Food Ordering System was rigorously evaluated based on its accuracy, responsiveness, recommendation quality, and system reliability. This section presents quantitative results obtained through systematic testing across each core module, along with tabulated performance metrics for clarity.

A. *Intent Classification and Chatbot Performance*

The system's natural language understanding module uses FastText embeddings with cosine similarity to classify user intents. Testing with a labeled dataset resulted in a classification accuracy of 92.7%, while the average cosine similarity score between predicted and true intent vectors was 0.86, demonstrating high semantic correlation. The chatbot module was evaluated over 100 diverse user interactions. It maintained a response success rate of 98% and an average response time of 0.8 seconds, ensuring fluid conversational experiences for end users. These performance indicators are summarized in Table I.

Table I: Intent Classification and Chatbot Performance Metrics

Metric	Value	Description
Intent Classification Accuracy	92.7%	Accuracy of FastText-based intent recognition
Average Cosine Similarity Score	0.86	Semantic similarity between input and intent vector
Chatbot Response Time	0.8 seconds	Average time to respond to a user query
Response Success Rate	98%	Percentage of queries correctly answered

B. *Health-Based Recommendation Quality*

To evaluate the personalized recommendation module, a group of users with varying health profiles tested the system's food suggestions. Based on expert reviews and user feedback, the average relevance score was found to be 8.6 out of 10, confirming the module's effectiveness in aligning food options with individual health needs.

C. *System Latency and Throughput*

The complete response cycle—including intent recognition, recommendation generation, API calls, and database queries—was measured for latency. The average end-to-end latency was 1.2 seconds, which remains well within acceptable bounds for real-time systems. The platform sustained performance with up to 50 concurrent users during load testing.

A consolidated overview of these results is presented in Table II.

Table II: Recommendation and System Performance Evaluation

Metric	Value	Description
Recommendation Relevance Score	8.6 / 10	Accuracy of food suggestions based on health profile
End-to-End System Latency	1.2 seconds	Total response time including backend processing
Concurrent User Support	50 users	Load testing capacity under stable performance

D. *Comparative Analysis*

Compared to traditional food ordering systems, the proposed system offers enhanced personalization, faster response times, and improved decision support through AI. The integration of user health data allows for more contextually appropriate food choices, a feature not typically offered by conventional platforms.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented a Smart Food Ordering System that integrates AI-driven personalization based on user health data, aiming to bridge the gap between convenience and nutritional relevance in modern food delivery platforms. By combining FastText-based intent classification, an interactive chatbot interface, and health-aware food recommendation algorithms, the system offers a user-centric solution that promotes healthier eating habits. The integration of modules such as real-time order tracking, payment processing, and geolocation validation further enhances its usability and practicality in real-world scenarios.

Experimental results demonstrated the system's effectiveness in terms of accuracy, response time, and recommendation relevance. The chatbot maintained a high response success rate with minimal latency, while the recommendation engine aligned closely with users' dietary needs. These outcomes confirm the system's potential for deployment in health-conscious and user-personalized food delivery ecosystems.

While the current implementation offers promising results, several enhancements can be made to further improve functionality and user experience:

1) Integration with Wearable Devices: Real-time health metrics from fitness trackers and smartwatches can enable dynamic food recommendations based on current physical activity or medical readings.
2) Advanced Nutritional Models: Incorporating deep learning models and external nutrition databases could allow more precise and medically informed food suggestions.
3) Multilingual Support: Expanding NLP capabilities to support multiple languages will make the system accessible to a broader user base.
4) Scalability and Deployment: Hosting the system on a cloud infrastructure will improve scalability, allowing for larger-scale adoption across regions and user groups.
5) Feedback-Driven Learning: Implementing a feedback loop from users to refine the recommendation engine over time can help improve personalization accuracy and satisfaction.

Overall, the proposed system lays the foundation for intelligent, health-focused food ordering applications and has strong potential for future research and commercial development.

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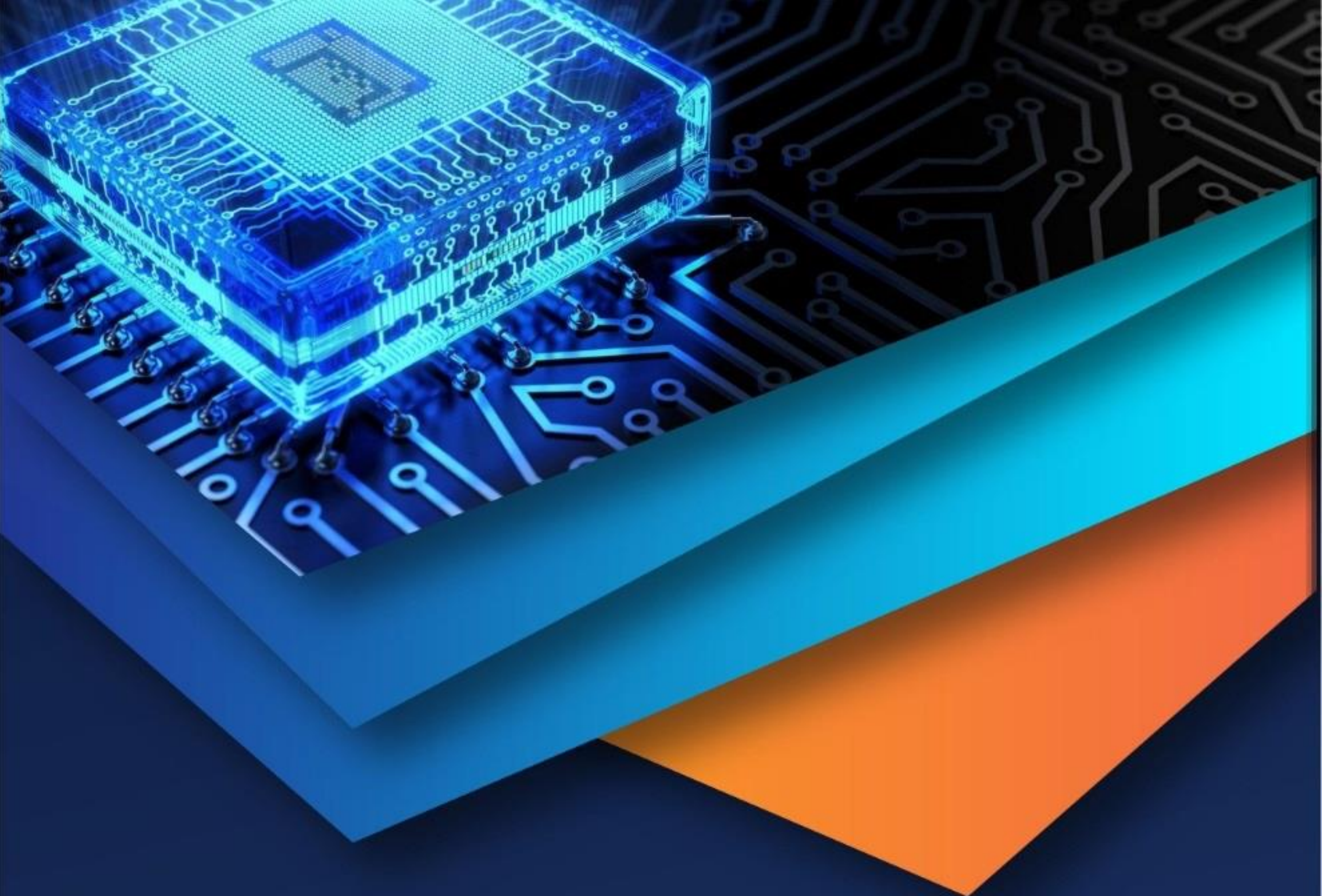

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