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DEPARTMENT OF
COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE)

Food Recommendation System Based on Taste Preferences

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Abstract

- Traditional recommendation systems struggle with personalization for individual taste profiles, prompting the development of a user-centric solution leveraging Machine Learning (ML) and Natural Language Processing (NLP).
- This innovative system allows users to describe desired flavors and ingredients, employing a Nearest Neighbor model to recommend similar dishes from a custom dataset, while NLP processes user input for model comprehension.
- With a user-friendly interface facilitating interaction, the system offers personalized recommendations based on taste preferences, thereby enhancing the user experience in food discovery.



Existing System

- ❑ **Swiggy:** Enhance user experience with personalized recommendations using ML and NLP, allowing customers to describe tastes and ingredients for tailored suggestions.
- ❑ **Zomato:** Improve food discovery by implementing ML and NLP-driven personalized recommendations, where users input flavor preferences for similar dish suggestions.
- ❑ **Dunzo:** Elevate user satisfaction by adopting ML and NLP technologies to offer personalized recommendations based on flavor and ingredient preferences for seamless food discovery.
- ❑ **EatSure:** Enhance menu exploration with ML and NLP-powered personalized recommendations, enabling users to describe tastes and ingredients for tailored dish suggestions.

Drawbacks of Existing system

- **Focus on Restaurants, Not Dishes:** These platforms primarily recommend restaurants based on factors like location, past orders, and overall ratings. They don't delve into the specifics of what a user might crave, making it difficult to find dishes that truly satisfy their taste preferences.
- **Limited Personalization:** Recommendations are often generic, based on popularity or past behavior. They don't account for the nuanced details of a user's taste, such as desired flavors, ingredients, or dietary restrictions.
- **Lack of User Input:** These systems typically don't allow users to directly express their cravings or preferences. Users are left browsing through menus or restaurant options without a way to narrow down choices based on their specific taste.
- **Inaccurate for New Users:** For new users with limited order history, recommendations might be irrelevant as the system lacks data on their taste preferences.

Literature review

Paper Title	Technology stack	Contribution	Limitation
[8] M. Rodriguez, P. Lee, and Q. Nguyen, "Balancing Exploration and Exploitation in Food Recommendation Systems: A Reinforcement Learning Approach," in <i>Proceedings of the International Conference on Machine Learning</i> , 2024, pp. 300-315	<ul style="list-style-type: none">❖ Reinforcement Learning Frameworks: TensorFlow, PyTorch❖ Data Processing: Pandas, NumPy❖ Model Deployment: Docker, Kubernetes	<ul style="list-style-type: none">❖ Reinforcement Learning Approach: Introducing a novel reinforcement learning-based method to balance exploration and exploitation in food recommendation systems, enhancing recommendation diversity and user satisfaction.	<ul style="list-style-type: none">❖ Algorithm Complexity: The reinforcement learning approach may introduce additional computational overhead and complexity, potentially limiting scalability and real-time performance in large-scale systems.❖ Algorithm Complexity: The reinforcement learning approach may introduce additional computational overhead and complexity, potentially limiting scalability and real-time performance in large-scale systems.

Literature review

Paper Title	Technology stack	Contribution	Limitation
[1] J. Smith, K. Johnson, R. Patel, and S. Gupta, "Advancements in Food Recommendation Systems: A Comprehensive Review," in <i>Proceedings of the IEEE International Conference on Data Mining, 2023</i> , pp. 100-115.	<ul style="list-style-type: none">❖ Machine Learning: TensorFlow, PyTorch❖ Natural Language Processing: NLTK, spaCy❖ Cloud Computing: AWS, GCP, Azure	<ul style="list-style-type: none">❖ Comprehensive Review: Offers an extensive overview of recent advancements in food recommendation systems, synthesizing insights from various methodologies and algorithms.	<ul style="list-style-type: none">❖ Time Constraint: Due to space limitations, may not delve deeply into each advancement or cover every emerging technology in the field.

Literature review

Paper Title	Technology stack	Contribution	Limitation
[4] E. Chen, F. Wang, and G. Zhang, "Context-Aware Food Recommendation Systems: A Survey," ACM Computing Surveys, vol. 45, no. 3, pp. 1-30, 2023.	<ul style="list-style-type: none">❖ Machine Learning: TensorFlow, scikit-learn❖ Natural Language Processing: NLTK, spaCy❖ Cloud Computing: AWS, GCP, Azure	<ul style="list-style-type: none">❖ Survey: Provides a comprehensive overview of context-aware food recommendation systems, highlighting key methodologies, techniques, and challenges in incorporating contextual information.	<ul style="list-style-type: none">❖ Scope Restriction: Due to space constraints, may not cover every aspect or recent development in context-aware food recommendation systems.

Problem Statement

We use Machine Learning and Natural Language Processing to understand user descriptions and recommend relevant dishes based on their expressed taste preferences, such as flavors and ingredients. Unlike other platforms, users actively describe their desired flavors, enabling a more personalized experience.

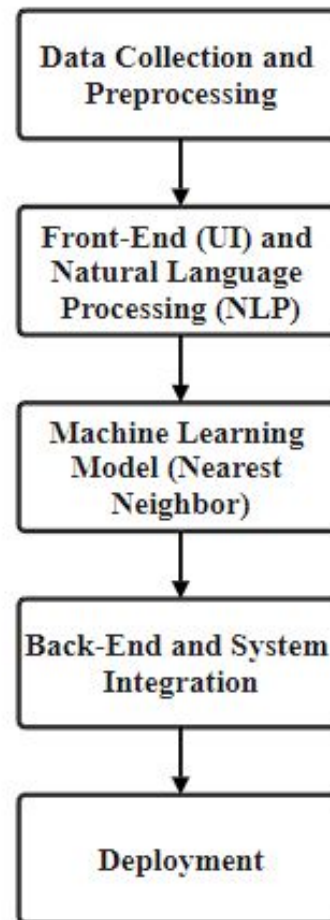
Proposed System

- **System Goal:** To provide personalized food recommendations using **ML** and **NLP** techniques.
- **User Interaction:** Users express their taste preferences through descriptions of flavors and ingredients.
- **ML Algorithm:** A **Nearest Neighbour algorithm** is trained on a dataset with food descriptions and user ratings.
- **NLP Application:** User input is processed by NLP to fit the model's requirements.
- **Technological Framework:** The system is developed with a combination of front-end and back-end technologies for ease of use.
- **Architecture Details:** The paper outlines the system's architecture, including dataset creation and algorithm selection.

Advantages of Proposed system

- **Personalized Recommendations:** Goes beyond popularity or past behavior to recommend dishes based on your unique taste profile expressed in natural language.
- **Improved User Experience:** Discover new dishes you'll love, eliminating decision fatigue when choosing food.
- **Dietary and Preference Flexibility:** Potentially incorporate dietary restrictions and cuisine preferences for even more tailored suggestions.
- **User-Friendly Interface:** Easy-to-use interface for effortless input of your desired flavors and exploration of recommendations.
- **Machine Learning Expertise:** Leverages the power of Machine Learning for accurate and evolving recommendations as data grows.
- Can find food spots directly by choosing food.

Implementation Details- Methodology



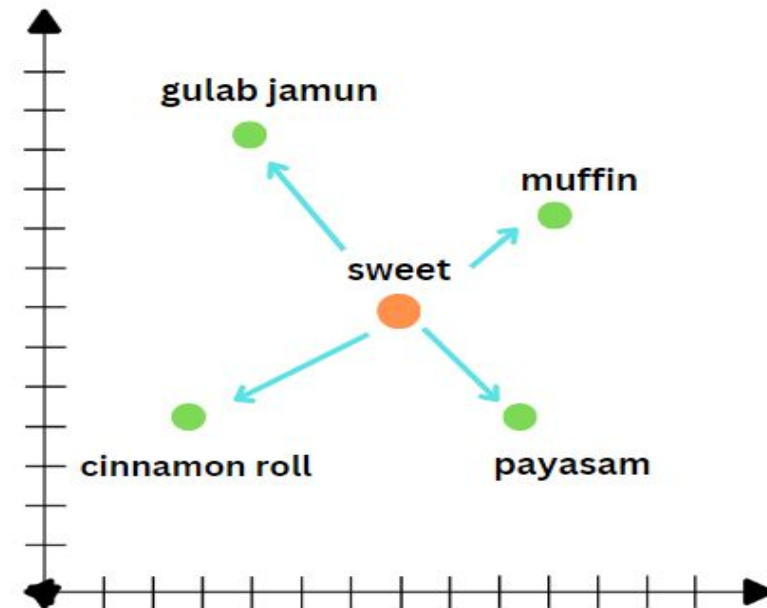
Implementation Details

User Interface (UI) and Natural Language Processing (NLP)

- **Front-End (UI):**
 - Develop a user interface using HTML, CSS, and JavaScript to allow users to input their desired flavor preferences in natural language.
 - Consider including options to specify dietary restrictions or cuisine preferences if desired.
- **Natural Language Processing (NLP):**
 - Utilize libraries like NLTK to perform tasks like tokenization (splitting text into individual words) and stop word removal (eliminating common words like "the" or "a").
 - Employ a pre-trained model like Universal Sentence Encoder from TensorFlow to convert user descriptions into numerical vectors suitable for the Machine Learning model.

Implementation Details : NN

**NEAREST
NEIGHBORS**



1. Data Preparation:

- The training data consists of a collection of data points, each representing an instance with features (attributes) describing it. These features can be numerical values or categorical variables.

2. Distance Metric Selection:

- A distance metric is chosen to quantify the "closeness" between data points. Common choices include:
 - Euclidean distance: Straight-line distance in a multidimensional space.
 - Manhattan distance: Sum of the absolute differences in features.

3. Prediction for a New Data Point:

- When a new, unseen data point arrives (testing data), the NN algorithm calculates the distance between the new point and all the data points in the training set using the chosen distance metric.
- The data point from the training set with the minimum distance is identified as the nearest neighbor.

Implementation Details

Back-End and System Integration

- **Back-End (Flask Framework):**
 - Use Flask to handle server-side operations, including communication between the user interface and the Machine Learning model.
 - The back-end receives user input from the UI, processes it using NLP, and sends the vector representation to the model.
 - The model returns recommendations, which are sent back to the UI for display.


Results & Discussion

TASTE	EXPECTED OUTPUT	PREDICTED OUTPUT
SPICY, SMOKY, HOT	TANDOORI CHICKEN	TANDOORI FISH, JAMBALAYA, CHICKEN BIRYANI, TANDOORI CHICKEN , MUTTON BIRYANI
TANGY, SPONGY, WARM	DHOKLA	POHA, EGG BHURJI, SOURDOUGH BREAD, DHOKLA , AMRITSARI KULCHA
SWEET, SOFT, WARM	MALPUA	MALPUA , ALOO GOBI, ALOO PARATHA, METHI THEPLA, PANDESAL
UMAMI, COLD, CHEWY	SUSHI	RAMEN, SUSHI , PAD THAI, PAD SEE EW, PUPUSA
TANGY, CRISPY, COLD	PANI PURI	PANI PURI , FISH AND CHIPS, MEDU VADA, RAVA DOSA, PEKING DUCK


Results

We helps you to **explore**
new foods through its
tastes


i want sweet foods | kochi [search](#)



Cinnamon Roll
enjoyed with Cream Cheese Frosting (Sweet) or Icing Sugar (Sweet)
[Find Spots](#)



Gulab Jamun
enjoyed with Vanilla Ice Cream (Cold) or Rabri (Creamy)
[Find Spots](#)




Muffin
enjoyed with Butter (Creamy) or Fruit Compote (Sweet)
[Find Spots](#)

Results


Gulab Jamun near kochi

Results ⓘ


Bikash Babu Sweets & Chaats
4.2 ★★★★★ (4,043)
Sweet shop · Kadikkal Buildings 54/40,
Kaloor - Kadavanthara Road Kadavanthara
Open · Closes 10:30pm
Menu highlight: gulab jamun




Cochin Halwa Centre
4.4 ★★★★★ (854) · ₹
Restaurant · Amaravathi Rd
Open · Closes 9:30pm
On the menu: gulab jamun



Bikash Babu Sweets
3.9 ★★★★★ (682)
Indian sweets shop · NH 47 Metro pillar
no.393, near iftar Hotel, opp. pittappillil
Agencies
Open · Closes 10pm
Menu highlight: gulab jamun



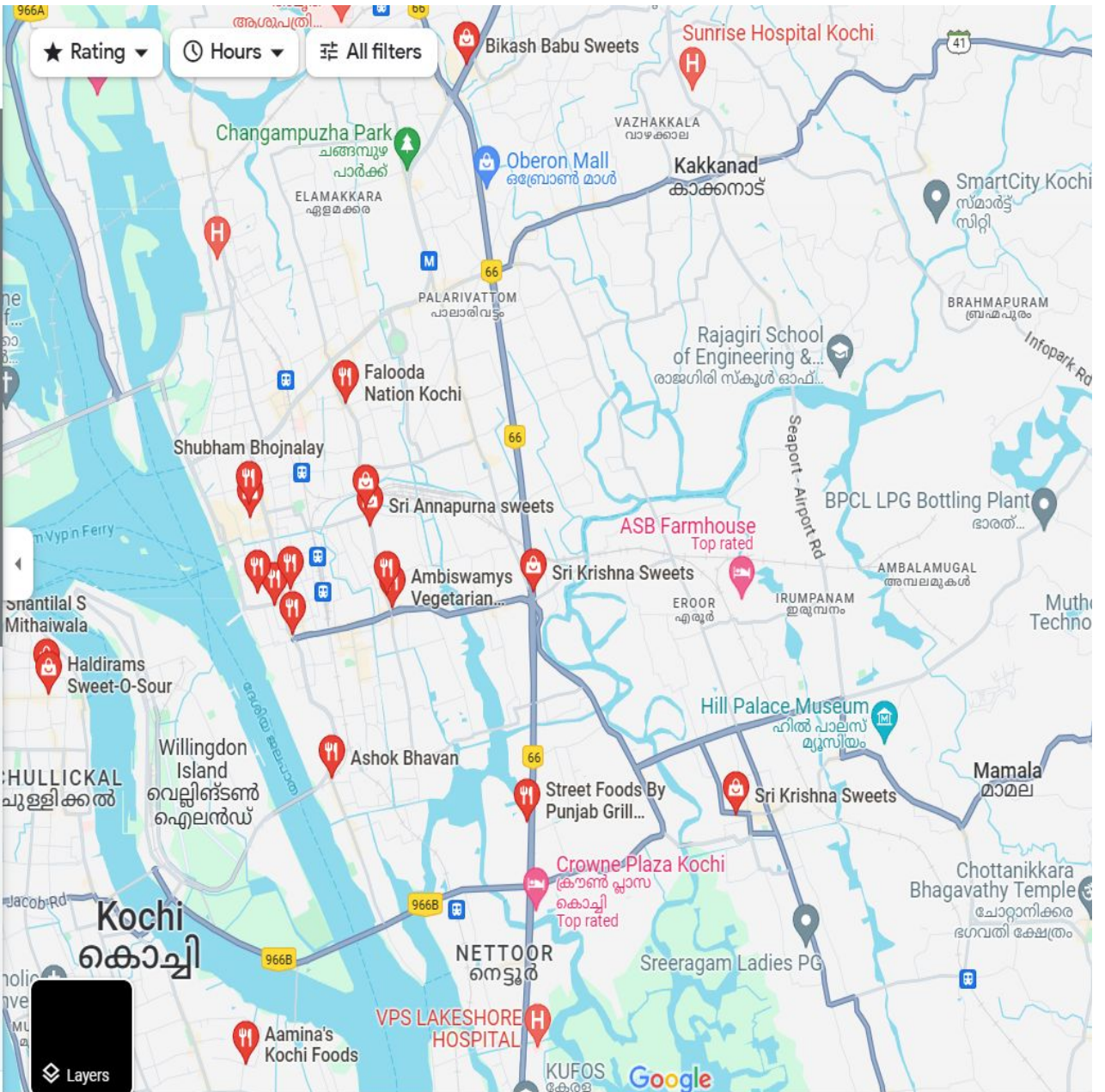
Haldirams Sweet-O-Sour
3.9 ★★★★★ (75)
Sweet shop · Sweet 'O' Sour, 6/2091,
Guarati Road. Mattancherry



★ Rating ▾

🕒 Hours ▾

🏠 All filters



Layers

Google

Food Recommendation System

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Conclusion

- This system personalizes food recommendations based on user-expressed taste preferences, leveraging machine learning and natural language processing.
- It addresses limitations of traditional recommendation systems with a user-centric approach.
- The system combines machine learning for analysis and NLP to understand user input.
- Recommendations are based on a nearest neighbor algorithm that considers similar user tastes.
- It's trained on a custom dataset of food descriptions and user ratings.
- A user-friendly interface is designed for easy interaction.
- As a future enhancement, the system could integrate functionalities to consider dietary restrictions and preferences.

Future Enhancements

- Integrating with restaurant reservation platforms to offer seamless dining experiences by providing recommendations that align with users' dining plans and preferences.
- Incorporating contextual information such as time of day, location, and social context to deliver more contextually relevant food recommendations.
- Customizing recommendations based on regional cuisines, dietary restrictions, or cultural preferences to cater to a diverse user base.
- Enabling voice-activated recommendation capabilities through virtual assistants or smart speakers to provide hands-free access to personalized food suggestions while cooking or meal planning.

Publication details

The process is ongoing.

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