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Survey on Vital : A Smart Supplement and Nutrition Recommendation System

Anmol Budhewar[1], Pratik Shinde[2], Om Sonawane[3], Ankit Patil[4], Pankaj Binnar[5]
[1] Assistant Professor- Dept. of Computer Engineering, SITRC Nashik
[2,3,4] B.E – Dept of Computer Engineering, SITRC Nashik
[1]anmolsbudhewar@gmail.com,[2]shindepratik624@gmail.com,[3]omsonawane1915@gmail.com [4]ankitpatil.eng@gmail.com
[5]pankajbinnar@gmail.com

Abstract: This paper presents Vital – a Smart Supplement and Nutrition Recommendation System, a web-based platform which is designed to provide personalised supplement recommendations and nutrition advice. To analyse user profiles and medical prescriptions, the system uses machine learning (ML), natural language processing (NLP), and optical character recognition (OCR). The user is able to input details such as age, gender, allergies, and health goals to get supplement suggestions that fit their needs. If a user uploads a prescription, the system checks it to find the medicines, connects them to health conditions, and creates nutrition advice using external APIs. The platform displays a full-stack implementation using React.js, Node.js, Python-based ML services, mongoDB which is combined with datasets and external APIs. Vital combines healthcare data and smart recommendation models to help people make correct health decisions. At the same time, it highlights the importance of consulting medical professionals before taking any supplements or medications.

Keywords: *Smart Supplement Recommendation, Nutrition Advice System, Machine Learning and NLP, Prescription Analysis (OCR), Personalized Healthcare Platform*

I.INTRODUCTION:

Healthcare is changed by new tech, as people need personalized ways to maintain their health and overall nutrition. The traditional methods for supplements usually don't consider personalized factors such as age, gender, allergies, and health-related conditions, which can give inaccurate outcomes. Newly emerging technologies—Machine Learning (ML), Optical Character Recognition (OCR), and Natural Language Processing (NLP)—enable the development of highly intelligent and accurate platforms that give back personalized and precise recommendations. This research introduces Vital — a Smart Supplement and Nutrition Recommendation System, which will use various new technologies to give back personalized supplement and nutrition recommendations.

1.1 Personalized Healthcare and Technology

ML models can analyze user profiles and medical histories to generate accurate recommendations, while NLP techniques interpret textual data like prescriptions, medical notes, and health goals.[1] OCR helps to automatically extract prescription information from uploaded images, reducing mistakes and making data entry easier.[2][13]

1.2 System Architecture and Data Integration

The system uses a set of modern tools: React.js for the user interface, Node.js and Python for server-side processing, and MongoDB for data storage that can grow easily. APIs add features by connecting to trusted nutrition and medicine databases, making sure the advice follows trusted rules.

1.3 Supplement and Nutrition Recommendations

Vital takes personal individual inputs such as age, gender, allergies, prescriptions, and health-related goals, which will help recommend specific supplement advice matching with the health.[3] Nutrition APIs will improve the product by giving nutrition recommendations by suggesting various suitable foods for that specific health issue. This feature will help people adopt better health habits.[4]

1.4 Research Gaps and Ethical Considerations

OCR helps read and extract prescription data from uploaded images, which reduces errors and makes entering data simpler. Most recommendation systems haven't been clinically tested, which raises concerns about their accuracy and reliability.[5] Because there are few lightweight mobile models, access is harder in low-resource areas. Ethical issues like data privacy, understanding how AI models work, and the need for professional medical advice must be considered to keep users safe and build trust.

II.LITERATURE SURVEY

Over the last decade, healthcare recommendation systems have improved a lot, going from simple diet tips to smarter, data-based platforms. Here, we review existing methods and explain the problems that inspired the development of better solutions such as Vital.

2.1 Generic Recommendation Systems

Early healthcare platforms mostly gave general diet and health advice without adjusting to each person's needs. This same-for-everyone approach did not consider important things like medical history, allergies, or personal health goals.[7]

2.2 Supplement Advisory Platforms

Multiple supplement-focused systems are present nowadays with similar drawbacks. Most of them do not integrate patient prescriptions or health conditions to improve the accuracy of the model, which could increase the risk of drug-nutrient-related issues. The lack of personalization in these platforms makes them much less reliable.[10]

2.3 Use of OCR and NLP in Healthcare

Technologies like Optical Character Recognition (OCR) and Natural Language Processing (NLP) are now used in healthcare to read and understand text from prescriptions and medical documents.[8][12] However, few systems combine OCR, NLP, machine learning, and nutrition APIs into one complete framework.[6][14]

2.4 Benefits of Personalization

Studies show that custom diet and supplement advice helps people stick to it better and leads to better health results than general advice.[9][15]

2.5 The Vital System's Contribution

Based on these results, the Vital system provides a combined method that brings together different data sources—including user profiles, prescriptions, structured datasets, and external APIs—into a complete recommendation system [11]

III.METHODOLOGY

The Vital system architecture combines modern web technologies, machine learning, and health data processing to provide personalized supplement and nutrition recommendations. The methodology is divided into several key components, described below.

3.1 Frontend Design

The frontend is built with React.js and Tailwind CSS, providing an interactive and easy-to-use interface. Users can enter information like age, gender, medical history, allergies, and personal health goals.

3.2 Backend Framework

The backend is built with Node.js and Express.js, which handle data processing and communication between components. This layer secures the transfer of user information between the frontend, machine learning modules, and external APIs. The backend is scalable, allowing the system to handle more users smoothly.

3.3 Machine Learning Engine

The recommendation logic is powered by Python-based machine learning modules. The workflow is structured as follows:

Query Embedding : A user query (q) is converted into a dense vector representation using embedding models such as SentenceTransformers or OpenAI embeddings:

$$q=f_{embed}(q)$$

Candidate Retrieval : Medicine embeddings (m_i) are stored in a FAISS index. The system computes cosine similarity to retrieve the top-(K) most relevant medicines:

$$sim(q,m_i)=\frac{q\cdot m_i}{|q||m_i|}'$$

Feature Construction : For each candidate, features are extracted, including text similarity, medicine metadata (price, composition, side effects), user profile attributes (age, conditions, allergies), and interaction features (allergy conflict, drug interaction flags) .

Re-Ranking : Candidates are scored using either (a) a rule-based system (fast baseline) or (b) a machine learning model such as LightGBM or a cross-encoder BERT:

$$s_i=f_{rank}(x_i)$$

Safety Filtering : Medicines with hard conflicts (e.g., allergy conflicts or life-threatening drug interactions) are discarded:

$$if\ allergy\_conflict = 1 \lor interaction\_severe = 1 \Rightarrow m_i\ is\ dropped$$

3.4 Database Management

User data such as profiles, prescriptions, and recommendation history will be stored securely in MongoDB Atlas. The database design will have high security and privacy by using various libraries for type checks, etc., which will ensure that it follows healthcare and data-handling standards.

3.5 External API Integration

This platform will integrate with a nutrition API to provide multiple food and nutrient-related information matching with the health issue to help users recover as fast as possible. These APIs will expand the system's ability to suggest various supplements and enhance the personalization feature of the web app.

3.6 System Architecture

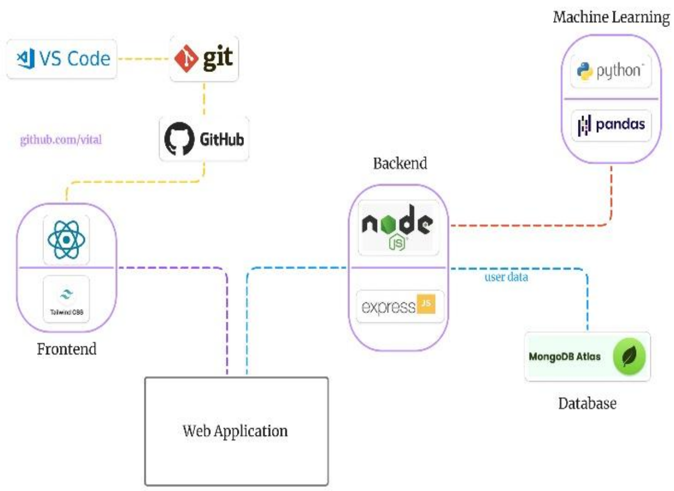

Figure 1*: System Architecture of Vital – Smart Supplement and Nutrition Recommendation System*

Figure 1 shows the main architecture of the Vital system, showing how the frontend, backend, database, and Python machine learning modules interact. It also highlights the use of VS Code, Git, and GitHub for development and version control, with clear data flow across all components.

IV.CONCLUSION

The Vital system combines Machine Learning, Natural Language Processing, and API-based nutrition data into a single web platform that gives custom supplement and diet advice. The current version focuses on user profiles and health goals, but adding Optical Character Recognition (OCR) for prescription analysis offers room for future growth, helping match medicines more accurately to health conditions. This method fixes the problems with general advice systems by making sure it is safe, personal, and trustworthy. Future updates may add mobile apps, connection with wearable devices, and improved AI models to make it easier to use and more useful in healthcare.

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