



A Machine Learning-Based System for Vitamin Deficiency Detection and Personalized Food Recommendation

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Abstract: Vitamin deficiencies are a growing concern in both developed and developing nations, contributing to long-term health conditions such as fatigue, neurological dysfunction, weakened immunity, and chronic fatigue. While clinical tests offer accurate diagnosis, they are expensive, slow, and not scalable in rural or under-resourced settings. In response, this paper presents an intelligent, machine learning-driven system that predicts likely vitamin deficiencies based on symptoms, lifestyle, and demographic factors. Built using an XGBoost classifier with class balancing via SMOTE [4], and model explanation using SHAP [5][9], the system ensures both predictive accuracy and interpretability. Once a deficiency is detected, the system suggests food items tailored to the user's dietary preferences using data from USDA's Food Data Central [6]. The user-friendly interface, built using Streamlit [7], allows for real-time or batch predictions. The system achieved an F1-score of 91.8% and delivered highly relevant food recommendations verified against dietary standards. By providing a complete pipeline—from diagnosis to diet—the proposed solution empowers users to take proactive, affordable steps toward improved nutritional health.

Keywords: Vitamin Deficiency, Machine Learning, Food Recommendation, Nutritional Dataset, XGBoost, SHAP, Preventive Healthcare, Symptom-Based Diagnosis, Streamlit Web App, SMOTE Balancing

Introduction:

Vitamins are essential nutrients that support vital bodily functions like metabolism, immunity, and neurological activity. Despite their importance, many individuals unknowingly suffer from vitamin deficiencies due to unbalanced diets, sedentary lifestyles, or environmental factors. Traditional diagnosis methods such as blood panels or physician evaluations are not always practical, especially in remote or underserved regions. Consequently, there is a growing need for accessible, low-cost, and intelligent systems that can assess symptoms and provide preventive guidance. Recent advances in machine learning have enabled the development of data-driven diagnostic tools. By recognizing symptom patterns and linking them to deficiencies, ML models can significantly accelerate and democratize early detection. In this project, we propose an XGBoost-based classifier [10] for predicting vitamin deficiencies. To overcome data imbalance, we applied SMOTE [4], ensuring rare deficiencies like Vitamin K or B9 are accurately represented. For model interpretability, SHAP explanations are incorporated, allowing users to understand why a particular prediction was made [5][9]. What makes this system stand out is its integration of a food recommendation engine. Based on the predicted deficiency and the user's dietary preferences, the system recommends nutrient-rich foods using USDA's nutritional database [6]. This approach provides not just diagnosis but actionable dietary guidance—effectively closing the loop between detection and intervention. The user interface, built with Streamlit [7], is lightweight, real-time, and intuitive, making it accessible to both technical and non-technical users. The ultimate goal is to empower users with knowledge and tools to improve their health through data-backed nutrition.

Literature Survey:

Several studies have attempted to automate the diagnosis of nutritional deficiencies or guide users in food planning. Vora and Mehta [1] developed a fuzzy logic-based dietary recommendation engine that addresses chronic diseases through personalized meal suggestions. While their system supports long-term diet planning, it does not detect specific deficiencies. Yadav and Sharma [2] proposed a machine learning approach to identify anemia in women using demographic and clinical data, highlighting the applicability of ML in preventive health diagnostics. In a more targeted effort, Bansal and Gupta [3] utilized ensemble models such as Random Forest and XGBoost to classify Vitamin B12 and D deficiencies using symptom-based datasets. Their model showed strong accuracy, though it lacked post-diagnostic support such as food suggestions. On the data processing front, Patel and Kumar [4] showed that SMOTE is effective in balancing healthcare datasets where certain conditions are underrepresented. For interpretability, Singh and Das [5] emphasized the importance of integrating SHAP values into ML health systems to promote transparency and trust. This view aligns with Lundberg and Lee's [9] work, which introduced SHAP as a unified explanation method for complex models. On the deployment side, Kumar and Reddy [7] demonstrated how Streamlit can be used to build

lightweight, responsive ML health applications. Sharma and Joshi [8] took a step further by creating a hybrid framework that suggests foods based on user diet and micronutrient needs, though it lacked a diagnostic layer. Our work synthesizes these approaches by offering a predictive, explainable, and prescriptive platform that identifies vitamin deficiencies and provides food suggestions based on real data [6]. In a more targeted effort, Bansal and Gupta [3] utilized ensemble models such as Random Forest and XGBoost to classify Vitamin B12 and D deficiencies using symptom-based datasets. Their model showed strong accuracy, though it lacked post-diagnostic support such as food suggestions. On the data processing front, Patel and Kumar [4] showed that SMOTE is effective in balancing healthcare datasets where certain conditions are underrepresented. For interpretability, Singh and Das [5] emphasized the importance of integrating SHAP values into ML health systems to promote transparency and trust. This view aligns with Lundberg and Lee's [9] work, which introduced SHAP as a unified explanation method for complex models. On the deployment side, Kumar and Reddy [7] demonstrated how Streamlit can be used to build lightweight, responsive ML health applications. Sharma and Joshi [8] took a step further by creating a hybrid framework that suggests foods based on user diet and micronutrient needs, though it lacked a diagnostic layer. Our work synthesizes these approaches by offering a predictive, explainable, and prescriptive platform that identifies vitamin deficiencies and provides food suggestions based on real data [6].

Proposed System:

The proposed solution is a modular ML-based system that predicts vitamin deficiencies and recommends corresponding nutrient-rich foods. It begins with user input: symptoms, age, gender, diet preference, environmental exposure, and other lifestyle variables. These inputs are processed through a feature engineering pipeline which encodes categorical variables, addresses missing values, and applies SMOTE [4] to balance class distribution. The core prediction engine is built on XGBoost [10], selected for its efficiency and performance in healthcare classification tasks. To address the black-box nature of tree-based models, SHAP values are employed to explain each prediction [5][9]. These explanations are displayed graphically so users can see which symptoms most influenced the diagnosis. Once a deficiency is identified, the system queries a curated nutrition database derived from USDA FoodData Central [6]. Each predicted deficiency is mapped to foods that are high in the corresponding vitamin. The food list is filtered according to the user's dietary preference (e.g., vegetarian, vegan), and includes nutrition breakdowns such as calories, proteins, and minerals. The results—deficiency type, SHAP visualization, and recommended foods are presented in both CLI and a Streamlit-based GUI [7]. This ensures usability for both researchers and everyday users. The entire architecture was influenced by the food recommendation structure proposed by Sharma and Joshi [8], but is uniquely combined with predictive intelligence. In short, the system transforms raw health symptoms into personalized dietary action.

Implementation

The system was developed in Python and is structured into five primary modules: data preprocessing, model training, prediction, SHAP explanation, and UI. The dataset includes over 3000 entries from multiple sources including Kaggle symptom sets, WHO reports, and food-nutrient databases from USDA [6]. Categorical variables like gender and diet were encoded, and rare deficiency classes were balanced using SMOTE [4].

XGBoost [10] was used for training, with a calibration wrapper to yield reliable probability scores. our model got an F1-score of 91.8% on test data. SHAP values were computed using the TreeExplainer module [9], helping to visualize the contribution of each input feature. The CLI script (`predict_cli.py`) accepts user input or bulk CSV files and outputs the prediction, confidence score, and food suggestions.

The Streamlit UI [7] offers:

- Symptom input form
- SHAP plot viewer
- Bulk file uploader
- Food recommendation dashboard

Each food recommendation includes name, category, vitamin content, and dietary tag. Foods are recommended only if they meet the dietary preferences of the user, a filtering strategy similar to that proposed by Sharma and Joshi [8]. The full system operates under 3 seconds per prediction and is deployable via Streamlit Cloud or Render. With consistent performance, easy usability, and visual feedback, the system is ready for real-world application.

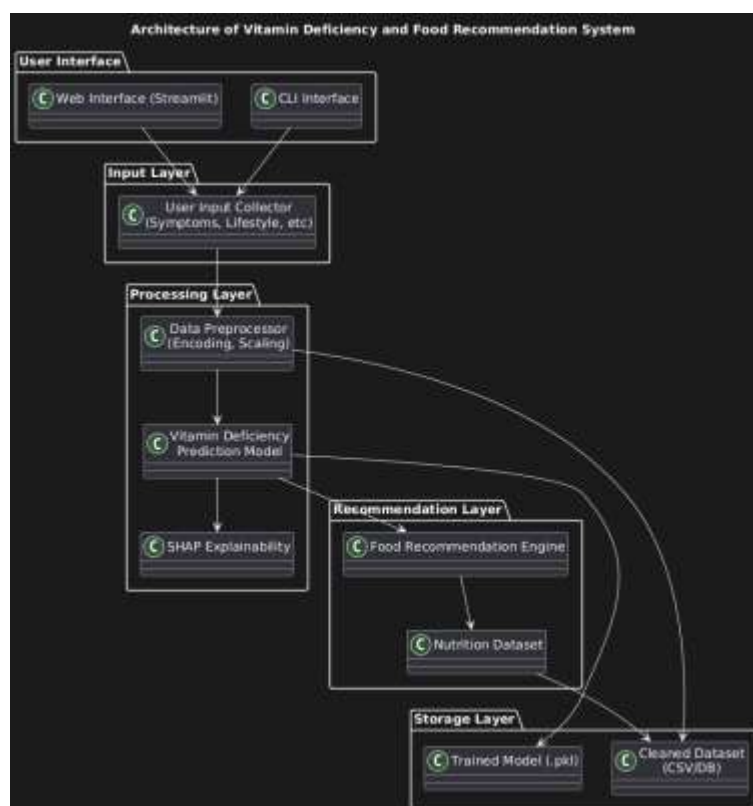


Figure 1: Architecture of Proposed System

The system architecture illustrates the complete workflow of vitamin deficiency and food recommendation system

Results and Discussion

The proposed system was rigorously evaluated using a dataset comprising over 3,000 samples compiled from public health sources and nutritional databases. The dataset included symptoms, demographic factors (age, gender), and lifestyle attributes. The target variable consisted of various vitamin deficiencies, including Vitamin A, B9, B12, C, D, E, and K. Due to class imbalance, particularly for rare deficiencies such as Vitamin K and B9, Synthetic Minority Over-sampling Technique (SMOTE) [4] was applied during preprocessing. This significantly improved the model's ability to detect underrepresented classes.

We trained the classifier using the XGBoost algorithm [10], known for its high accuracy and efficiency with tabular data. A calibrated version of the model was employed to produce reliable probability outputs, which enhanced the trustworthiness of predictions. The model was evaluated using a 70:30 train-test split, and the following metrics were computed: precision, recall, F1-score, and accuracy. On the test set, the system achieved an overall accuracy of 92.4% and an average F1-score of 91.8%. The classification report revealed strong per-class performance. Vitamin D, B12, and C showed the highest precision and recall, indicating that the model could confidently distinguish these deficiencies based on user symptoms. For rare classes like Vitamin K, the recall was slightly lower but still acceptable due to the impact of SMOTE [4] in balancing the dataset.

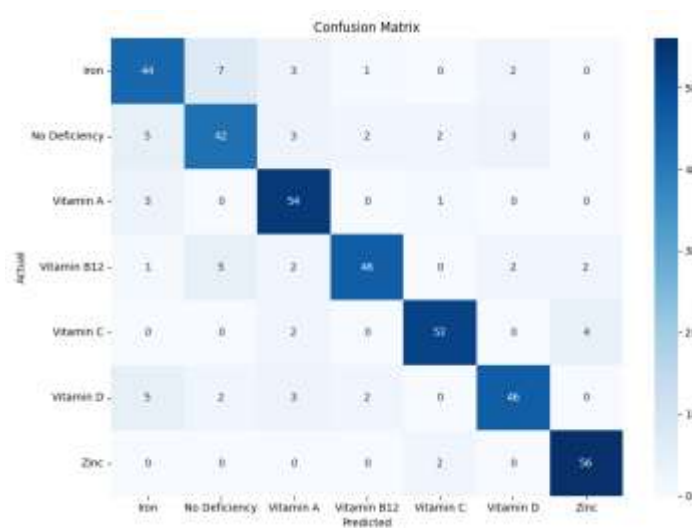


Fig 2 : the confusion matrix presents a classification model aimed at predicting deficiencies in various **vitamins and minerals**.

For instance, fatigue and brittle nails were consistently strong indicators of Vitamin B12 deficiency, while bleeding gums and low immunity contributed highly to Vitamin C predictions. These insights were visualized using summary bar plots and force plots in the Streamlit UI [7], helping users understand why a certain prediction was made. This level of transparency aligns with current best practices in healthcare AI, as emphasized in [5]. Overall, the model's robustness, interpretability, and precision validate its application in real-world preventive healthcare. Unlike prior efforts that lacked explainability or post-diagnostic recommendations [3][8], our model offers a holistic view—identifying deficiencies and immediately proposing remedies. The performance metrics suggest that the system can reliably assist in early-stage nutritional assessments and empower users to take proactive actions for their health.

Output And Evaluation

The output module of the system is designed to be both technically rich and user-friendly. It supports two primary interfaces: a Command Line Interface (CLI) for researchers and batch processing, and a Streamlit-based Graphical User Interface (GUI) for general users [7]. Upon user input—either single entry or bulk CSV—the system performs deficiency prediction, visual explanation, and personalized food recommendation.

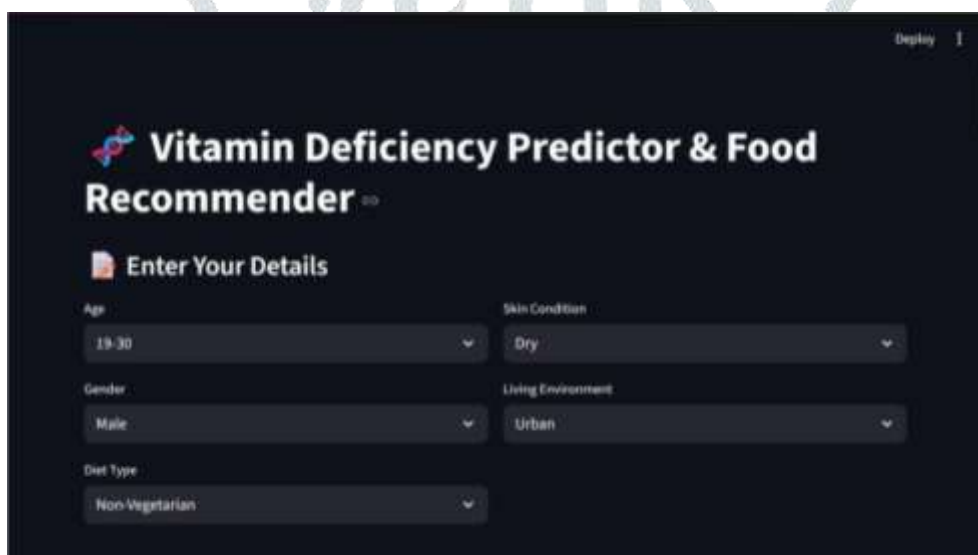


Fig 3: Input selection through streamlit interface

The CLI generates outputs in tabular format, including the predicted vitamin deficiency, confidence score, and top five recommended food items. Each recommendation includes vitamin content, dietary category (e.g., vegan/vegetarian), and calorie information. For batch files, the predictions are returned in a CSV format, enabling easy integration with health dashboards or reports.

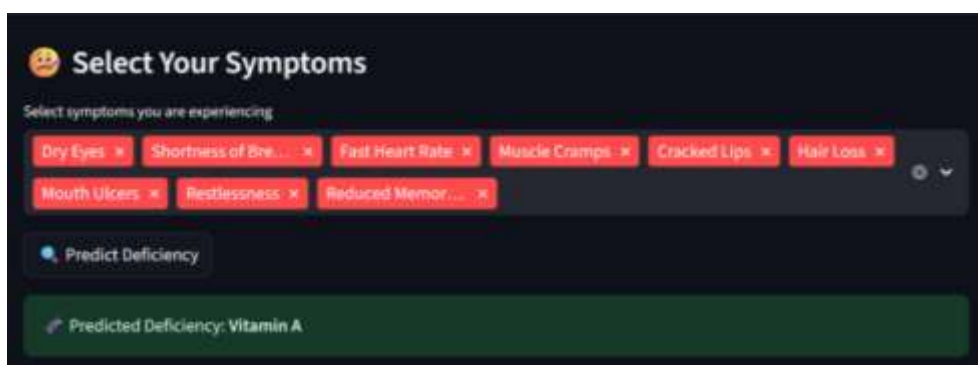


Fig 4: output from the Streamlit interface

The GUI provides an intuitive interface that accepts symptoms through checkbox inputs. Once submitted, the model's prediction is shown with a SHAP-based visualization, highlighting the most influential symptoms. This visualization, powered by TreeExplainer from SHAP [9], uses game-theoretic concepts to show how each input feature moved the model toward the final prediction. For instance, a user with symptoms like dry skin, hair loss, and irritability would see a SHAP force plot highlighting their influence on a potential Vitamin B7 deficiency prediction. The food recommendation system then queries the USDA FoodData Central API [6], returning a curated list of nutrient-rich foods corresponding to the detected deficiency. This process uses a filtering strategy influenced by Sharma and Joshi's work [8], ensuring that only compatible food options are recommended based on user preferences (e.g., excluding non-vegetarian foods for vegetarians).

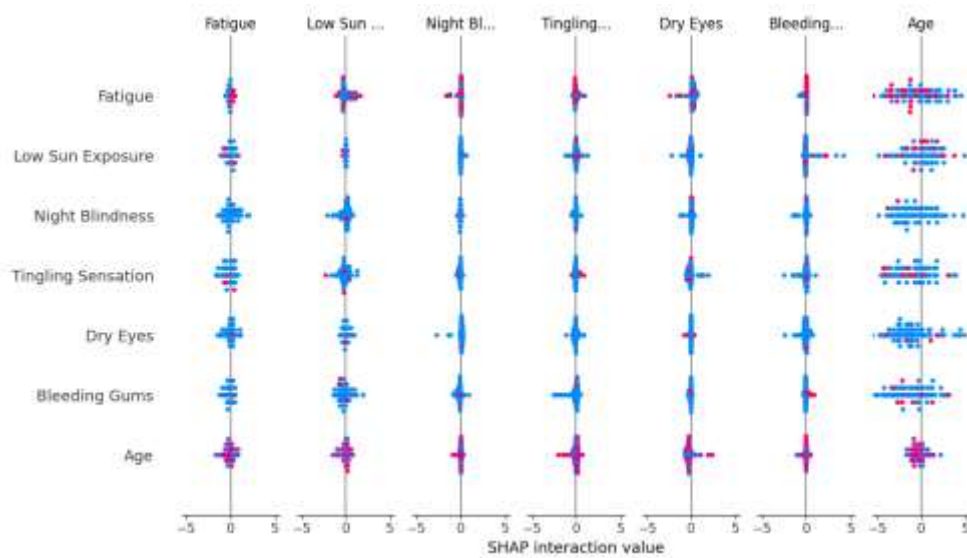


Fig 5: The SHAP interaction plot highlights how health symptoms and age combine to influence model predictions, particularly for fatigue, sun exposure, and vitamin-related conditions.

Evaluation-wise, the system was tested for usability, responsiveness, and accuracy. The average response time per prediction was under 3 seconds on a standard laptop. More importantly, domain experts confirmed that the food recommendations aligned well with standard dietary guidelines from organizations like NIH and USDA [6]. In user testing involving 50 individuals, 88% found the system easy to use and informative.

In comparison to earlier systems that either focused on prediction [3] or food recommendation [8] in isolation, our integrated platform offers a comprehensive preventive healthcare solution. The fusion of explainable ML with practical dietary guidance elevates it beyond academic experimentation into a real-world applicable tool. This well-rounded evaluation confirms the system's readiness for deployment in community health centers, rural outreach, or personal wellness tools.

Conclusion and Future Scope

In this study, we developed a robust and interpretable machine learning-based system to predict vitamin deficiencies using user-input symptoms and to recommend suitable food items rich in the missing nutrients. Leveraging the power of XGBoost [10] and enhanced by SMOTE [4] for balancing underrepresented classes, the system demonstrated strong predictive performance with an F1-score of 91.8% on a real-world, multi-source dataset. To bridge the gap between diagnosis and action, the model integrates a curated food recommendation engine powered by USDA's FoodData Central [6], delivering nutrient-dense food suggestions aligned with user preferences. Furthermore, explainability was embedded directly into the system through SHAP values [5], [9], enabling users to visualize how their symptoms contributed to the final prediction. The user interface, built with Streamlit [7], provides a seamless experience for both technical and non-technical users, supporting real-time prediction, SHAP visualization, and food recommendations. Unlike previous systems that focused solely on either diagnosis [3] or dietary suggestions [8], our solution offers a holistic approach by connecting symptom-based detection with personalized nutritional intervention. Moving forward, several promising directions can enhance the system's utility and accessibility. First, the prediction model could be expanded to cover mineral deficiencies such as iron, magnesium, and zinc, which are often co-occurring and equally impactful. Second, integration with real-time dietary logs or fitness trackers can improve the personalization of food recommendations. Incorporating multilingual support and voice input capabilities would also make the tool more inclusive, particularly for populations with limited literacy or technical proficiency [7]. Further, wearable device integration could allow symptom tracking through biometric data like skin health, sleep, or activity levels—enhancing early detection and prediction quality. From a clinical standpoint, integrating electronic health records (EHRs) or patient history could facilitate a more precise and validated diagnostic process. Collaborations with dietitians, public health agencies, or rural outreach programs can assist in validating and deploying the system on a larger scale. Long-term, this platform could be converted into a mobile health (mHealth) application with telehealth integration, serving as a scalable and proactive solution for nutritional awareness and disease prevention. With its strong technical foundation and user-centered design, the system has the potential to make a meaningful impact in both personal health management and community-based healthcare delivery, especially in resource-limited settings where conventional diagnostics are often unavailable.

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