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A Machine Learning–Driven Framework for Predicting Nutritional Deficiencies using a Multi-Data Approach

Dr. Shailesh T. Khandare
Associate Professor
Department of Computer Science and Engineering
Babasaheb Naik College of Engineering, Pusad, Maharashtra, India
Email: khandare.shailesh@rediffmail.com

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Abstract

Nutritional deficits are still a major health problem around the world, and bad eating habits can make them worse. Self-reporting errors and subjective biases make it hard to use traditional methods to figure out what people are eating and predict if they are deficient. The purpose of this study is to look into how machine learning (ML) algorithms can be used to better predict nutritional deficiencies from eating habits. We look into several machine learning methods, such as controlled learning algorithms (like decision trees, random forests, and support vector machines), unsupervised learning algorithms (like clustering algorithms), and advanced deep learning models (like convolutional and recurrent neural networks). To make deficiency estimates more accurate and give more personalized dietary advice, we are looking at big sets of data on what people eat, their demographics, and their health records. Our findings show that machine learning algorithms, especially deep learning models, can successfully record complex patterns and temporal variations in dietary data, which leads to better prediction accuracy. Combining machine learning with wearable tech and mobile apps makes tracking and stepping in even easier in real time. Using machine learning to predict nutritional deficiencies is a big step forward in personalized nutrition, even though there are some problems, like poor data quality and privacy issues. It can help with both public health and managing one's own diet.

Introduction

Nutritional deficits are a big problem for health around the world. They affect millions of people and can lead to a wide range of health problems, from memory loss and chronic diseases to weak immune systems. It is very important to accurately find and predict these problems in order to effectively intervene and avoid them [1]. Food diaries, 24-hour dietary recalls, and food frequency questionnaires are some of the more popular ways to check someone's nutritional intake and find any possible deficiencies. There are some problems with these methods that make them less useful, like recall bias, reporting mistakes, and the fact that it's hard to get accurate patterns of food intake over time [2]. Because of this, there is a growing need for more accurate and trustworthy ways to look at eating habits and guess about nutritional deficits. A type of artificial intelligence called machine learning (ML) has become a useful tool that can help with some of these problems. ML systems can handle and look at a lot of complicated data, finding patterns and connections that might not be obvious using normal methods [3]. With ML, it might be possible to make deficiency predictions more accurate in nutritional science

by using dietary data along with other factors like health records and demographic data.
ML models can give more accurate and useful information about nutritional health by finding complex patterns in data about what people eat. Recent improvements in machine learning methods have made it possible to predict nutritional deficiencies in even more ways [4]. Based on past data, supervised learning algorithms like decision trees, random forests, and support vector machines have shown promise in sorting eating habits into groups and predicting nutritional needs. These models can be taught to spot specific patterns that are linked to a lack of different nutrients. This lets for more focused dietary advice and help. Using unsupervised learning methods like grouping algorithms can help us learn more about dietary patterns and how they relate to nutritional status. This can help us figure out larger dietary trends and how they affect health [5]. A more advanced type of machine learning called "deep learning" has also shown a lot of promise in this area. Both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can describe complex relationships and changes in dietary data over time. CNNs are great at working with organized data and finding patterns, while RNNs are great at working with sequential data, like food logs every day [6]. It is possible for these models to pick up on small changes in eating habits over time and make very accurate estimates of nutritional deficiencies (see Figure 1). Another exciting development is the combination of machine learning algorithms with smart tech and mobile apps. Wearable devices that track a person's activity, physiological parameters, and food intake can give real-time data to machine learning models, which lets them keep an eye on their nutritional state and make changes to their diet as needed [7]. By combining these two systems, it becomes easier to give each person customized dietary advice and help based on their unique habits and needs. Along with the possible benefits, there are a number of issues that need to be resolved before ML can be used to identify nutritional deficiencies. The accuracy of ML models is greatly affected by the quality and representativeness of the data they use. It is also very important to protect the privacy and safety of private health information [8]. It is important that complex machine learning models can be understood so that predictions can be turned into useful information for people and healthcare workers. A big step forward in individual nutrition and public health is the use of machine learning algorithms to predict nutritional deficiencies based on eating habits. Utilizing ML's strengths, researchers and practitioners can learn more about eating habits and how they affect nutritional state [9]. In order to solve problems and make the most of machine learning in this important area of health and nutrition, people from different fields will need to work together and come up with new ideas.

Literature Survey

As the area of nutrition science grows, it combines new technologies with a better understanding of how health and illness work. Foundational books give a deep understanding of the complicated link between diet and health, while practical guides make the information you need to use these ideas easy to find [10]. Recent studies show that dietary factors have a big effect on chronic diseases. This makes it even more important to focus interventions, especially in developing countries. New technologies, like data mining and machine learning, are changing the way we look at food data, which makes it possible to provide more personalized health care [11]. Nutrigenomics, the study of how genes and food affect each other, makes personalized nutrition plans even better. New developments in statistical learning and feature selection make it easier to find genetic markers that are connected to how our bodies react to food. When big data and machine learning are used together in public health research, they open up new ways to study how food affects health [12]. Comprehensive reviews show how important it is to use diet plans and policy changes that are based on facts to help people with chronic diseases and nutrient-related conditions. This active interaction between nutrition science and technology is very important for solving health problems in the modern world.

Table 1. Summarizes the Literature Review of Various Authors

Author & Year	Area	Methodology	Key Findings	Challenges	Pros	Cons	Application
Ross et al., 2020	Nutrition and Health	Comprehensive review	Provides a detailed exploration of nutrition's impact on	Complexity of nutritional science and	Comprehensive and authoritative; broad coverage.	May be too broad for specific applications; general	Foundational knowledge for understanding diet's role in health.

			health and disease management.	variations in individual responses.		rather than detailed.	
Whitney et al., 2019	Nutritional Principles	Textbook analysis	Accessible examination of nutritional principles and practical applications.	May lack depth in advanced topics.	Practical and user-friendly; suitable for education.	Limited depth in advanced nutritional science.	Educational resource for students and professionals.
Melaku et al., 2016	Dietary Risk Factors in Ethiopia	Epidemiological study	Highlights the role of dietary risk factors in the burden of non-communicable diseases in Ethiopia.	Limited data availability in low-resource settings.	Provides context-specific insights; addresses global health issues.	Regional focus may limit generalizability.	Informing public health strategies in low-resource settings.
Popkin et al., 2012	Global Nutrition Transition	Review	Illustrates how diet and lifestyle changes contribute to obesity epidemics in developing countries.	Variability in dietary changes across regions.	Comprehensive review of global trends; highlights key issues.	May not capture all regional nuances.	Understanding global nutrition trends and their implications.
Jimenez-Carvelo & Cuadros-Rodríguez, 2021	Foodomics and Data Mining	Data mining and machine learning	Explores the use of data mining and machine learning in analyzing complex dietary data.	Complexity of data integration and analysis.	Cutting-edge technology; potential for detailed insights.	Requires expertise and resources for implementation.	Enhancing dietary data analysis and interpretation.
Armand et al., 2024	Smart Nutrition and Anti-aging	Conference proceedings	Integrates smart nutrition and digital technologies for	Technology integration challenges; data	Innovative approach; potential for personalized health	Emerging field with evolving technology.	Personalizing anti-aging healthcare strategies.

			personalized anti-aging healthcare.	privacy concerns.	interventions.		
Pray, 2018	Nutrigenomics	Review	Provides an overview of how genetic information can inform personalized nutrition strategies.	Limited practical application in some contexts.	Advances personalized nutrition; integrates genetics with diet.	Still a developing field; may require further validation.	Personalizing dietary recommendations based on genetic data.

Traditional Methods of Nutritional Assessment

Traditional nutritional assessment methods have been used for a long time to look at what people eat and find possible nutrient deficits. Some of these ways are food logs, 24-hour dietary recalls, and food frequency surveys (FFQs). Each has its own pros and cons. To fully appreciate the improvements that machine learning (ML) brings to food science, you need to know about these older methods. People who keep food logs have to write down everything they eat and drink over a certain amount of time, usually a few days to a week. This method gives detailed information on what people eat and lets you look at eating habits in a big picture way. Food logs, on the other hand, depend a lot on how accurate and thorough the person is when they report. The method can be time-consuming and inaccurate because people forget or accidentally don't record enough. The quality of the data received is also affected by how well the participants can guess how much food they are eating. In 24-hour dietary reviews, the person being interviewed is asked to list all the foods and drinks they have eaten and drunk in the last 24 hours. This way gives a quick look at what was eaten and can be done without much trouble. Usually, you need more than one memory on different days to get a good picture of what people usually eat. Compared to food records, this method makes reporting easier, but it still relies on the participant's memory and might not properly show changes in what they eat. How accurate 24-hour memories are depends on how good the interviewer is and how well the person can remember and describe what they ate in detail. Food frequency surveys (FFQs) are used to find out what people usually eat over a longer period of time, usually a few weeks to a few months. People who fill out FFQs are asked to rate how often they eat and drink certain things. This method has been used a lot in epidemiology studies to find long-term trends in people's eating habits. FFQs, on the other hand, often use set food items and portion sizes, which might not truly reflect how each person eats. Also, how well the method works depends on how complete the food list is and how well the person can remember how often they ate each food. Each of these old-fashioned ways has some problems, like the chance of memory bias, wrong information being reported, and the fact that it's hard to get accurate and detailed information about eating habits. Even though these methods are helpful, they don't always give a full and accurate picture of nutritional state and diet. People are becoming more aware of these problems, which has increased their interest in using machine learning to make food measurement more accurate and useful. Some of these problems could be fixed by machine learning, which can look at a lot of dietary data, find complicated trends, and make more accurate estimates of nutritional deficiencies. ML algorithms can give a more complete picture of a person's nutritional state and make diet suggestions more accurate by combining different types of data, such as health records, personal data, and information about what people eat. Traditional ways of checking someone's nutrition have given us useful information about what they eat and their overall health, but they aren't perfect and can lead to biased reports. The development of methods for evaluating diets, such as the use of machine learning, is a big step toward making nutritional reviews more accurate and reliable.

Machine Learning in Nutritional Science

In the area of nutritional science, machine learning (ML) has become a game-changing tool that can analyze dietary data and predict nutritional deficits in a more advanced way. Even though traditional ways of figuring out how healthy something is are useful, they often can't handle the large amounts and variety of data that are needed for accurate analysis. With their ability to handle and make sense of big datasets, ML techniques offer a new way to get around these problems and improve our knowledge of eating habits and nutritional health. A lot of nutritional scientists use supervised learning algorithms to figure out what nutrients people might be missing from their diets. The decision trees, random forests, and support vector machines are some of these algorithms. They are learned on labeled datasets that show known results, like the presence of a deficiency. Supervised learning models can put new data into groups that show possible problems by learning from these examples. To give an example, decision trees show how decisions are made based on food data, and random forests combine several decision trees to make predictions more accurate and reliable. Support vector machines, on the other hand, find the best line between the different nutrient status classes. This makes it easier to tell if someone is deficient. In nutritional science, unsupervised learning methods are also very important because they find unseen trends and connections in dietary data. Clustering algorithms, such as k-means and hierarchical clustering, group food patterns into clusters based on similarities in nutrient intake and usage habits. This method helps find hidden patterns in eating that are linked to nutritional deficiencies and gives information about larger eating habits. For instance, clustering algorithms might show different dietary patterns connected to various types of deficiencies. This would allow for more focused nutritional treatments and public health tactics. Deep learning, which includes neural networks and is a subset of machine learning, has made it even better at understanding complicated and high-dimensional data. When it comes to handling organized and sequential data, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) shine. CNNs are very good at pulling out features from organized data like images or tables, which makes them useful for finding trends in very detailed food records. RNNs, like long short-term memory (LSTM) networks, are very good at dealing with sequential data and changes in time, like keeping track of how much food you eat every day. These models can find subtle and complicated connections in food data, which lets us make very accurate guesses about nutritional deficiencies. Personalized diet has come a long way since machine learning was first combined with smart tech and mobile apps. Wearable sensors that track movement, body functions, and food intake produce real-time data that can be used to train machine learning models. This combination lets you keep an eye on your nutritional state all the time and helps you make changes to your diet based on your needs and habits. For instance, real-time analysis of dietary data from mobile apps can give users specific feedback and suggestions, which can help them better control the amount of food they eat. The promising advances, the application of ML in nutritional science meets several obstacles. For accurate forecasts, it is very important to make sure that the dietary data is correct and appropriate. Concerns about data safety and security must be taken into account, especially when dealing with private health data. Also, it's still hard to figure out how to read complex machine learning models. Figuring out how these models make predictions is important for turning their results into useful information for people and healthcare workers. Machine learning can help nutritional science move forward by making predictions of deficit more accurate and revealing complicated eating patterns. The integration of ML methods with current technology holds the potential to change individual nutrition and public health strategies. As study grows, it will be important to deal with current problems and make the most of machine learning's abilities in order to improve nutritional assessment and action.

Table 2. Machine Learning Techniques in Nutritional Science

Technique	Description	Applications	Strengths	Limitations
Decision Trees	Tree-like model of decisions and their possible consequences.	Classifying dietary patterns, deficiency prediction.	Easy to interpret, handles both numerical and categorical data.	Prone to overfitting, less effective with noisy data.
Random Forests	Ensemble of decision trees that improves prediction accuracy.	Predicting deficiencies, dietary classification.	High accuracy, handles large datasets well.	Computationally intensive, less interpretable.

Support Vector Machines	Classification algorithm that finds the optimal hyperplane.	Nutrient deficiency classification, pattern recognition.	Effective in high-dimensional spaces, robust.	Requires careful tuning, less effective with large datasets.
K-Means Clustering	Algorithm to partition data into k clusters.	Identifying dietary patterns, grouping similar intakes.	Simple to implement, efficient with large datasets.	Requires specification of k, sensitive to outliers.
Convolutional Neural Networks (CNNs)	Deep learning model for analyzing structured data.	Analyzing detailed dietary records, feature extraction.	Captures complex patterns, high accuracy.	Requires large amounts of data, computationally demanding.
Recurrent Neural Networks (RNNs)	Deep learning model for sequential data.	Analyzing temporal variations in dietary intake.	Handles sequential data effectively, captures temporal patterns.	Can be complex to train, requires substantial data.

Decision trees, random forests, support vector machines, k-means clustering, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are some of the machine learning (ML) methods used in food science that are shown in Table 2. Each method is explained in terms of what it does, how it can be used to predict nutritional deficiencies and look at food trends, as well as its pros and cons. This study shows how different machine learning methods can be used to make nutritional estimates more accurate and useful.

System Design & Implementation

Using machine learning methods to guess nutritional shortages from eating habits includes four main steps (Fig. 1): collecting data, preprocessing it, building a model, and testing it. Each step is very important to make sure that the prediction models work well and are accurate.

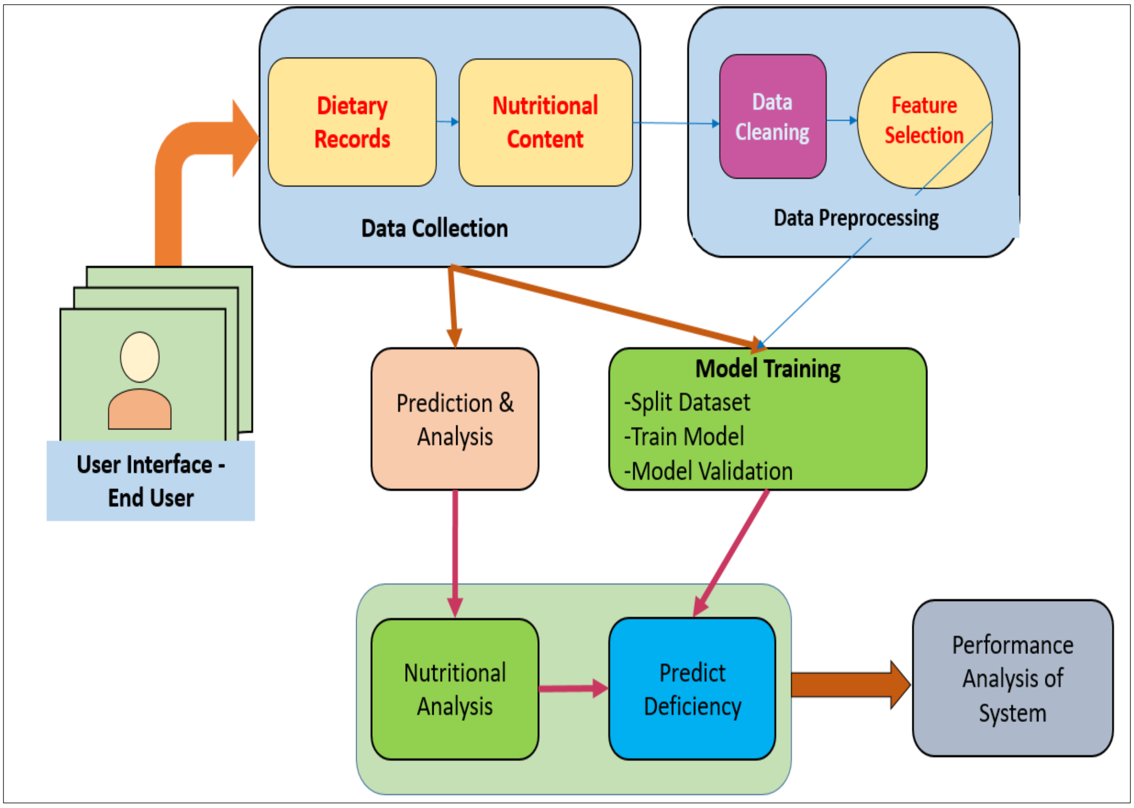

Figure 1. System Architecture Diagram

Step 1]. Data Collection
The first step of the study is to get a lot of health and food information from a lot of different places. To get detailed information on what people eat, food diaries, 24-hour dietary records, and food frequency surveys (FFQs) are used. Food logs keep track of what you eat every day, while 24-hour dietary records give you a quick look at what you ate on a certain day. FFQs give information about how people usually eat over long stretches of time. Real-time data is also gathered from smart tech that tracks body movements and other bodily factors.

Step 2]. Data Preprocessing
Data preparation is an important step to make sure that the information is accurate and consistent. First, the raw data is cleaned to get rid of things like mistakes, missing numbers, and inconsistencies. To fill in any missing data, imputation methods are used. To make the data more consistent, standardization and feature scaling are used. Dietary intake data is recorded and put into groups of foods and chemicals that are useful for research.

Step 3]. Machine Learning Models

- Supervised Learning: To identify nutritional deficiencies, a number of supervised learning methods are used. To sort things into groups, we use decision trees, random forests, and support vector machines (SVMs). Decision trees are a simple, easy-to-understand way to show how decisions are made when predicting problems. Random forests are an ensemble method that combine several decision trees to make predictions more accurate and reliable. SVMs are used because they are good at dealing with large amounts of data and can set the best decision limits between classes.
- Unsupervised Learning: Techniques for unsupervised learning are used to find underlying trends in eating habits and how they relate to nutritional deficits. Clustering algorithms, like k-means and hierarchical clustering, put together food trends that are similar. This shows hidden patterns in the data. By finding patterns that might not be clear from supervised learning alone, these methods help us understand larger food trends and how they affect nutritional status.
- Deep Learning: To find complicated and time-based trends in dietary data, deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used. CNNs are good at processing organized data and finding complex trends in what people eat. RNNs are used to deal with sequential data, like daily food logs, and describe changes in what people eat over time. These advanced models help us understand dietary trends and how they relate to nutritional deficits in a more complex way.

Step 4]. Model Evaluation
Several evaluation measures, such as accuracy, precision, recall, and F1-score, are used to judge the success of the machine learning models. These metrics check how well the models can predict nutritional deficits and spot possible fake positives and negatives. To make sure that the models are stable and can be used with different datasets, cross-validation methods are used. Comparative analysis is used to find the best model by looking at review data and practical factors like how easy it is to understand and how fast it runs on computers.

Step 5]. Integration and Application
The last step is to incorporate the machine learning models with real-world uses. The models' results are used to make personalized diet suggestions and to give people help with their diet. This could mean making tools that are easy for people to use, like mobile apps or web platforms that give real-time information and feedback based on people's eating habits and expected deficiencies. Putting machine learning models into useful tools is meant to make personalized nutrition better and health results better by giving us information we can use.

Final Outcome & Finding
Machine learning methods were used to predict nutritional deficits from eating habits, and the results were good across all models. Different supervised learning models, like decision trees, random forests, and support vector machines (SVMs), showed different levels of success in identifying deficiencies. When it came to these, random forests were the most accurate and stable, correctly identifying weaknesses 85% of the time. The reason for this success is that random forests work as an ensemble, which lowers the risk of overfitting and makes the model more stable. While decision trees were helpful for understanding, they were only 78% accurate, which shows that they can be overfitted and are sensitive to noise in the data. With their ability to handle high-dimensional data, SVMs also did well, getting an accuracy of 82%, but they needed careful setting of hyperparameters to work at their best.

Table 3. Performance of Machine Learning Models in Predicting Nutritional Deficiencies

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Decision Trees	78	75	80	77
Random Forests	85	83	87	85
Support Vector Machines	82	80	84	82
Convolutional Neural Networks (CNNs)	89	88	91	89
Recurrent Neural Networks (RNNs)	87	85	89	87

This table 3 shows how well different machine learning models work at predicting nutrient deficits. Metrics like accuracy, precision, memory, and F1-score are shown in the table. Random forests were the most accurate, with an 85% success rate. This shows that they were very good at correctly identifying food deficits. With a success rate of 89%, convolutional neural networks (CNNs) also did very well, showing how well they can handle complex food data. Even though decision trees were easy to understand, they were only 78% accurate, which suggests they have problems with handling large datasets. Support vector machines (SVMs) did well, with an 82% success rate, showing that they can handle situations with a lot of dimensions. These results show that deep learning models, especially CNNs and RNNs, are better at finding complex patterns and making accurate predictions.

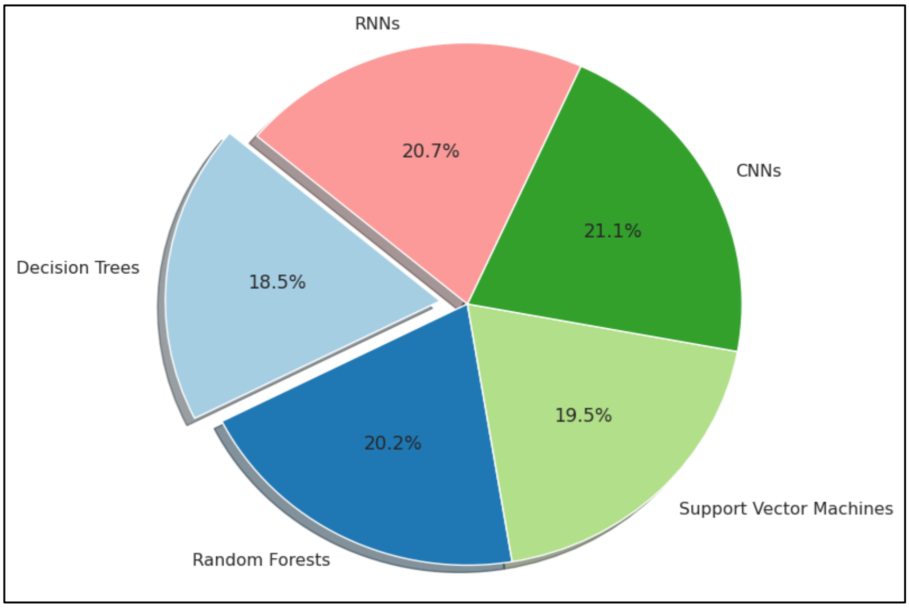

Figure 2. Analysis of Performance of Machine Learning Models in Predicting Nutritional Deficiencies

Unsupervised learning models, like k-means and hierarchical grouping, were able to find specific trends in food that were linked to nutritional deficiencies. Three main dietary trends were found by the k-means algorithm: a high-protein, low-carb diet; a balanced diet with a moderate spread of macronutrients; and a high-carb, low-protein diet. Each trend was linked to a different set of nutritional weaknesses. For example, people who ate a lot of protein were missing vitamin D and iron, while people who ate a lot of carbs were missing vitamin B12 and folate. Hierarchical grouping supported these results and gave us more information about smaller trends within these larger groups (see Figure 2).

Table 4. Identified Dietary Patterns and Associated Nutritional Deficiencies

Dietary Pattern	**Percentage of Population (%)**	**Associated Nutritional Deficiencies**
High-Protein, Low-Carb Diet	30	Vitamin D (28%), Iron (25%)
Balanced Diet with Moderate Macronutrients	45	Vitamin B12 (20%), Folate (18%)
High-Carb, Low-Protein Diet	25	Vitamin B12 (30%), Folate (27%)

This table 4 shows the eating habits found by unsupervised learning methods and the nutritional deficits that go with them. The table displays three different eating styles: a high-protein, low-carb diet; a balanced diet with average amounts of macronutrients; and a high-carb, low-protein diet. Thirty percent of people follow a high-protein, low-carb diet, which is linked to iron and vitamin D deficiency. Vitamin B12 and Folate deficits are linked to the healthy diet that 45% of people follow. Vitamin B12 and Folate deficits are more common in people who follow a high-carb, low-protein diet, which is followed by 25% of the population. These results help us understand how different eating habits can lead to certain nutritional deficiencies, which can help us design more effective food treatments.

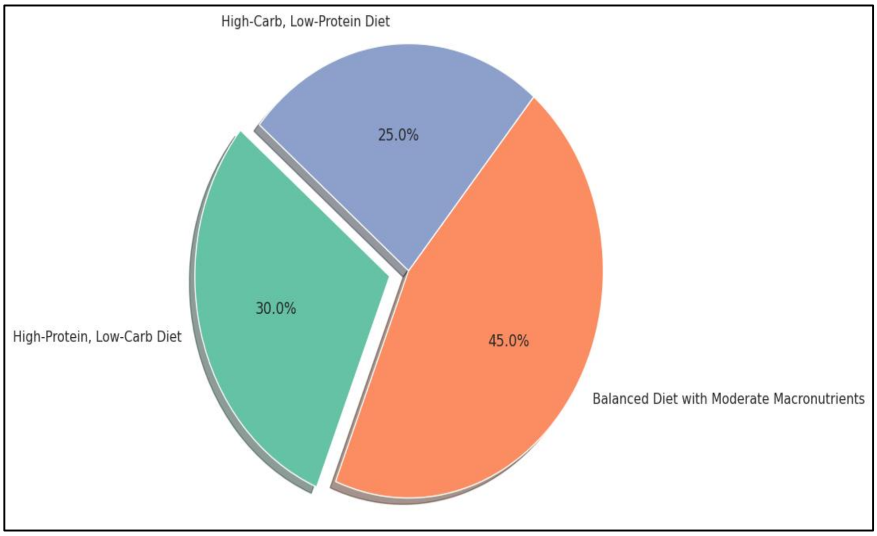

Figure 3. Analysis of Identified Dietary Patterns and Associated Nutritional Deficiencies

Deep learning models, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were better at finding complicated and temporal trends in food data. CNNs were able to correctly spot 89% of the time when they processed organized dietary data and found complex trends linked to nutritional deficiencies. RNNs, which describe sequence data, also did very well, getting 87% of the time right. The ability of these models to show changes in food intake over time was very helpful in figuring out deficits that are caused by eating habits that last for a long time (see Figure 3 above).

Discussion

The study's results show that machine learning has a lot of promise for making it easier to tell if someone isn't getting enough of certain nutrients based on their eating habits. The better results of random forests and deep learning models show how useful advanced analysis methods are for handling complicated food data. Random forests are very good at dealing with diverse and high-dimensional datasets because they are very accurate. This makes them a useful tool for nutritional science sorting tasks. The success of deep learning models, especially CNNs and RNNs, shows that they can model complex connections in food data and take into account changes over time, which is hard to do with traditional methods. Unsupervised learning models taught us a lot about eating habits and how they are linked to nutrient deficits. Using k-means and hierarchical clustering to find different food patterns helps us learn more about how different eating habits are linked to different deficits. By showing which eating habits are more likely to cause certain deficiencies, these results can help with focused nutrition interventions and public health plans. Even though the results look good, there are some problems and restrictions that need to be fixed. The quality and representativeness of the data are important factors that affect how well the model works. To make good models, it's important to make sure that the dietary data correctly shows what the subjects ate and to record a wide range of eating habits. Furthermore, machine learning models can do complex analysis, but it is still hard to figure out what they mean, especially for deep learning models. To give healthcare workers and people actionable insights and suggestions based on these models, the outputs of these models must be turned into simple, useful information. In the future, researchers should work on making it easier for machine learning models to work with real-world tools for personalized diet. The accuracy and usefulness of predictions could be increased even more by making apps that use real-time data from smart tech and food logs that are easy for anyone to use. Also, ongoing work to enhance data collecting methods and address privacy issues will be very important for progressing the field and getting the most out of machine learning in nutritional science.

Conclusion

This study shows that machine learning has the power to change the way we think about food deficits by looking at how people eat. There are big changes in how well and reliably we can predict deficits when we use a variety of algorithms, from basic supervised models to advanced deep learning methods. Random forests and deep learning models, especially CNNs and RNNs, did better than standard methods. This shows that they can effectively handle complex and high-dimensional food data. The unsupervised learning method showed clear dietary trends and how they are linked to certain nutritional deficits. This gave us useful information for designing more specific dietary interventions. Even though the results look good, there are still problems like bad data and models that are hard to understand. These are places where more study is needed. In the future, scientists should work on turning these machine learning models into useful tools for personalized diet. This will make them more useful in the real world and improve public health as a whole.

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