AVE Trends in Intelligent Computing Systems

A Smart Diet Recommendation System Integrating Machine Learning and Lifestyle Analysis

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Abstract: Diet prevents obesity, diabetes, hypertension, and cardiovascular disease and improves mental and physical health. Traditional diet planning often relies on generic guidelines or dietitian consultations that may not account for lifestyle, eating habits, or health issues. Universal strategies rarely work, restricting their ability to encourage good behaviour. User-specific data informs our machine learning-based Diet Recommendation System. Diet, fruit and vegetable consumption, fast food consumption, physical activity, exercise regimens, and other lifestyle factors are considered. Individualised nutritional advice is based on age, gender, height, weight, and BMI. Divide people into Balanced, Weight-Loss, High-Protein, and Low-Carbohydrate diets using Random Forests, XGBoost, and SVMs. Preprocessed structured datasets ensure consistent model training and validation, as well as precision and reliability. The technology accurately predicts and provides dependable, individualised dietary advice tailored to users' lives and interests, according to experiments. This technology leverages data-driven intelligence and nutrition science to make diet planning more successful, scalable, and accessible, especially for individuals without nutritional coaching. The study shows how machine learning may make diet planning dynamic, user-centric, and health-focused, helping people eat healthier. User comments and updated recommendations can enhance the algorithm as health and habits change. Diets work because they adapt to life.

Keywords: Diet Prediction; Machine Learning; Dietary Habits; Lifestyle Patterns; Random Forest; XGBoost and SVM Models; Support Vector Machine (SVM); Health Recommendation; Cardiovascular Disorders.

Cite as: S. R. Bose, J. A. Jeba, N. C. Evangeline, R. Regin, P. Parmasvian, and S. S. Jeev, "A Smart Diet Recommendation System Integrating Machine Learning and Lifestyle Analysis," *AVE Trends in Intelligent Computing Systems*, vol. 2, no. 4, pp. 230–240, 2025.

Journal Homepage: https://www.avepubs.com/user/journals/details/ATICS

Received on: 22/01/2025, **Revised on:** 13/05/2025, **Accepted on:** 19/07/2025, **Published on:** 12/12/2025

DOI: https://doi.org/10.64091/ATICS.2025.000215

1. Introduction

A nutritious, balanced diet plays a vital role in maintaining overall health and preventing a wide range of lifestyle-related diseases, including diabetes, obesity, hypertension, cardiovascular disease, and metabolic disorders. In the modern era, people are increasingly dependent on fast food and processed meals due to their busy schedules and convenience-driven lifestyles. Combined with sedentary habits and limited physical activity, these dietary patterns have led to a surge in chronic health conditions across all age groups. Consequently, there is a growing need for personalised dietary recommendations tailored to an individual's unique nutritional requirements, health goals, and daily routines. Traditional diet planning methods typically rely on general nutritional guidelines, manual consultations with dieticians or nutrition experts, or predefined diet charts. While these approaches can be effective, they often lack personalisation, accessibility, and adaptability to changing habits or preferences. Moreover, regular consultations can be time-consuming, costly, and difficult to access in rural or underprivileged regions. Hence, there is a clear opportunity to develop automated, data-driven systems that efficiently and cost-effectively provide personalised, evidence-based diet recommendations. In this context, Machine Learning (ML) emerges as a powerful and intelligent solution. ML techniques can analyse large datasets containing information about individuals' eating habits, daily activities, physical profiles, and demographic factors such as age, gender, and occupation. By identifying patterns and correlations within these datasets, ML models can predict optimal diet plans that align with a person's health objectives and lifestyle.

Unlike traditional one-size-fits-all recommendations, ML-based systems continuously learn and adapt from new data, making them dynamic, flexible, and increasingly accurate over time. This research proposes a machine learning-based framework that classifies individuals into specific dietary categories such as Balanced Diet, Weight-Loss Diet, High-Protein Diet, and Low-Carbohydrate Diet, depending on their personal lifestyle choices and nutritional habits. The study uses well-established, robust ML algorithms, including Random Forests, XGBoost, and Support Vector Machines (SVMs). These algorithms are chosen for their high performance, reliability, interpretability, and computational efficiency, making them ideal for real-world dietary classification tasks. The primary objective of this study is to design and implement a predictive model that can deliver accurate, practical, and scalable diet recommendations for individuals. The system aims to help users make healthier, more informed food choices, thereby contributing to the prevention and management of lifestyle-related diseases. By leveraging machine learning, this framework has the potential to make personalised nutrition guidance accessible to a broader population, supporting the global shift toward preventive healthcare and wellness-oriented living. The proposed model not only enhances the accuracy of dietary recommendations but also promotes long-term behavioural changes toward healthier living. Ultimately, this research demonstrates how technology and data-driven intelligence can transform personalised nutrition into an accessible, impactful tool for public health improvement.

2. Literature Review

Opie et al. [1] discussed dietary recommendations for the prevention of depression, emphasising the strong link between nutrition and mental health. Their study highlighted that consuming nutrient-rich foods such as fruits, vegetables, whole grains, and lean proteins plays a major role in improving mood and cognitive function. By identifying the impact of diet quality on emotional well-being, their research laid the foundation for the development of personalised nutritional systems to promote both physical and mental health. Tapsell et al. [2] explored the interrelationships among foods, nutrients, and dietary patterns, focusing on how these elements influence the creation of modern dietary guidelines. Their work emphasised that effective nutrition planning should consider overall dietary patterns rather than single nutrients, as interactions among different food components are vital for maintaining health. This approach supports the development of machine learning models that simultaneously analyse multiple lifestyle and dietary variables to generate more comprehensive and realistic diet recommendations. Behrens et al. [3] evaluated the environmental impacts of adopting dietary recommendations and examined how food consumption patterns affect sustainability. Their study showed that diet planning should not only ensure health benefits but also consider environmental outcomes such as carbon emissions and resource usage. This holistic perspective aligns with data-driven approaches such as machine learning, which can balance health objectives with ecological considerations when formulating personalised diet plans. Rehman et al. [4] introduced "Diet-Right," an intelligent food recommendation system that applies computational intelligence techniques to generate personalised dietary suggestions. The system collects and analyses user data, including health and lifestyle parameters, to recommend appropriate food choices. This research demonstrated the potential of artificial intelligence to automate nutrition planning and paved the way for integrating machine learning algorithms into dietary prediction systems for personalised healthcare. Herforth et al. [5] conducted a global review of food-based dietary guidelines, assessing how various countries formulate and present nutritional recommendations.

Their study highlighted the importance of cultural, social, and regional contexts in shaping dietary patterns. These findings underscore the need for flexible, adaptive diet recommendation systems that can adjust to diverse demographic and cultural factors—an idea that complements the adaptability of machine learning models. de Faria Coelho-Ravagnani et al. [6] examined dietary recommendations during the COVID-19 pandemic, emphasising the importance of maintaining a balanced diet to support immunity and overall health. Their work identified the role of healthy dietary habits in disease prevention and recovery, especially during health emergencies. This research supports the development of intelligent diet prediction systems that can adapt to changing health circumstances and guide individuals in maintaining optimal nutrition during challenging times. Lock et al. [7] analysed the health, agricultural, and economic effects of adopting healthy diet recommendations. Their findings revealed that shifting to balanced, sustainable diets not only improves individual health outcomes but also enhances agricultural efficiency and economic stability. This study highlights the interconnectedness among diet, health, and socioeconomic systems, underscoring the importance of scalable, data-driven solutions, such as machine learning, for large-scale dietary policy implementation. Lichtenstein et al. [8] investigated patients' adherence to dietary recommendations for patients with Type II Diabetes Mellitus. Their study revealed that while most patients understood the importance of diet in managing diabetes, actual compliance was low due to lifestyle challenges, lack of motivation, and social factors. The findings emphasised the need for ongoing nutritional education and personalised meal planning to improve long-term adherence and glycemic control. Cámara et al. [9] presented a nutrition diet recommendation system based on users' interests and health conditions. The system employed data-driven approaches to provide personalised food recommendations aligned with user preferences. Their study demonstrated that integrating user data with nutritional science can enhance engagement and improve adherence to healthy dietary habits, thereby enabling smarter, technology-assisted diet planning. Comerford et al. [10] presented the American HeartAssociation's revised diet and lifestyle recommendations, focusing on promoting cardiovascular health through balanced nutrition and regular physical activity. Their research emphasised limiting saturated fats, maintaining a healthy body weight, and incorporating nutrient-dense foods.

These principles provide a strong scientific foundation for modern diet prediction models that aim to personalise recommendations based on cardiovascular and metabolic risk factors. Rivellese et al. [11] conducted a comparative analysis of food-based dietary guidelines across different regions to update the AESAN Scientific Committee's recommendations. Their study examined the similarities and differences in global dietary guidelines and emphasised the importance of continuous updating based on scientific evidence. This comparative approach is valuable for machine learning-based systems, which rely on diverse datasets to refine and update their diet prediction accuracy over time. Meier and Christen [12] performed a global review of dairy recommendations included in food-based dietary guidelines. Their study evaluated the role of dairy products in balanced nutrition, highlighting their contribution to essential nutrients such as calcium and protein. The findings suggested that dairy intake should be personalised based on health needs, tolerance, and dietary preferences. This perspective aligns well with machine learning-driven diet systems, which can analyse individual data to recommend appropriate levels of dairy and other nutrients for optimal health. Butti and Gangappa [13] examined the environmental impacts of various dietary recommendations and eating styles, using Germany as a case study. They compared various diet models—such as vegetarian, vegan, and mixed diets—and assessed their carbon footprint and resource use. Their results suggested that adopting sustainable dietary habits not only benefits human health but also significantly reduces environmental degradation and greenhouse gas emissions. Iwendi et al. [14] proposed a machine-learning-based IoMT (Internet of Medical Things)-based patient diet recommendation model. The system analysed patient health parameters to recommend suitable dietary plans in real time. Their approach showed high efficiency in improving patient monitoring and automating dietary guidance, marking a major advancement in healthcare technology for diet management (Figure 1).

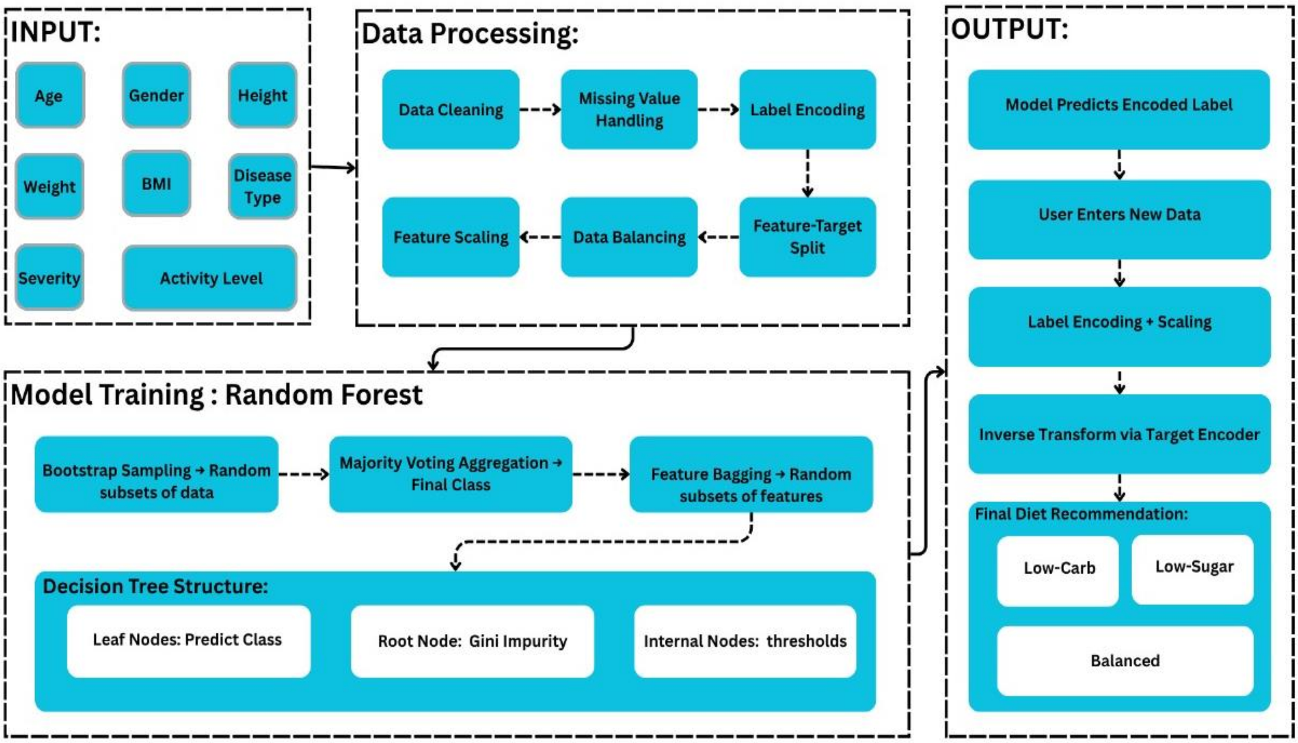

Figure 1: Block diagram of diet prediction

De Abreu et al. [15] examined adult compliance with dietary recommendations and found that most individuals failed to meet the recommended intake levels for fruits, vegetables, and whole grains. Their study identified key demographic and behavioural factors driving poor adherence, highlighting the urgent need for public health strategies that encourage healthier food choices and sustained behavioural change (Figure 2).

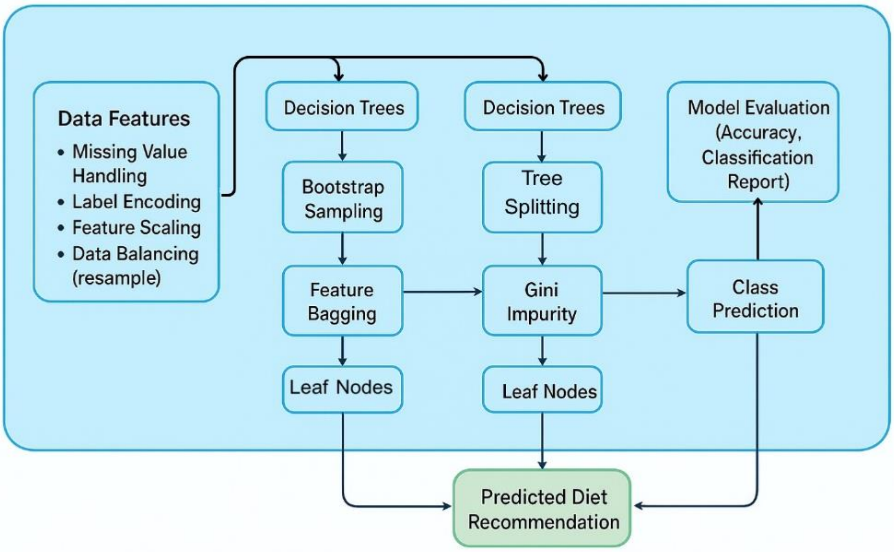

Figure 2: Architecture diagram of diet prediction

3. Methodology

The proposed Diet Recommendation System is a comprehensive, data-driven framework that generates personalised dietary recommendations based on a wide range of health, lifestyle, and behavioural factors. Unlike traditional diet planning, which often relies on generalised guidelines, this system leverages machine learning algorithms to provide specific, adaptive, and evidence-based recommendations. By integrating intelligent data analysis with structured preprocessing techniques, the system ensures that each diet plan is accurately tailored to meet the individual's nutritional needs and long-term wellness goals. This approach not only improves recommendation accuracy but also promotes sustainable health outcomes across diverse population groups. The system begins by collecting extensive user data, including physiological parameters and behavioural indicators. The physiological data includes essential demographic and biometric variables such as age, gender, height, weight, and Body Mass Index (BMI). These serve as the foundation for understanding the user's basic health profile. The system further incorporates medical information, including details on disease type and severity, as well as clinical parameters such as blood pressure, glucose levels, and cholesterol levels, which provide critical insights into the user's metabolic and cardiovascular health. Such comprehensive health metrics allow the model to identify risk factors and tailor diet plans accordingly. In addition to health data, the framework also captures lifestyle-related variables that influence dietary needs and metabolism.

Factors such as daily caloric intake, physical activity level, exercise duration, and work routine intensity are analysed to understand the user's energy expenditure and nutritional balance. The inclusion of behavioural patterns, such as meal frequency, sleep duration, and hydration levels, adds further depth to the personalisation process. Moreover, the system considers individual preferences and constraints to ensure the generated diet plans are both realistic and sustainable. This includes inputs like dietary restrictions (e.g., vegetarian, vegan, lactose-free), food allergies, preferred cuisines, and cultural eating habits. It also evaluates past adherence patterns—how consistently a user follows a given diet—to refine future recommendations and enhance user engagement. By combining clinical, behavioural, and preference-based factors, the system creates a holistic understanding of each individual. Before training the machine learning models, the collected dataset undergoes a comprehensive preprocessing phase to ensure data reliability, consistency, and quality. This process includes data cleaning, normalisation, feature scaling, handling missing values, and encoding categorical variables. Outlier detection and removal techniques are also applied to eliminate noise and bias from the data. Once preprocessed, the refined dataset provides a strong foundation for ML algorithms to learn meaningful patterns and correlations, ultimately leading to more accurate, explainable, and trustworthy diet recommendations:

$$\mathrm{BMI} = \frac{\mathrm{Weight_{kg}}}{(\mathrm{Height_m})^2} \qquad (1)$$

Equation 1 states that, in fields such as Disease Type or Dietary Restrictions, null values are replaced with "None," thereby maintaining dataset integrity. Non-numeric attributes such as Gender, Cuisine, and Activity Level are converted to machine-readable values using Label Encoding. The data is then standardised using a StandardScaler to align all features on a comparable numerical scale, thereby improving model efficiency and convergence. Real-world data often suffers from class imbalance, where some diet categories are more common than others. To address this, the system uses random oversampling to equalise class representation. This technique ensures that minority diet classes receive sufficient attention during training, preventing the algorithm from favouring majority classes and thereby enhancing overall performance across all diet categories. The heart of the predictive process relies on a Random Forest Classifier, an ensemble model known for its strength and interpretability in classification tasks.

The dataset is split into training and testing subsets in an 80:20 ratio, allowing the model to learn and validate effectively. The algorithm employs 200 decision trees, each with a maximum depth of 15, and uses regularisation parameters min_samples_split = four and min_samples_leaf = 2 to prevent overfitting while maintaining model flexibility. Through iterative learning, the Random Forest identifies intricate patterns and nonlinear relationships between health metrics and dietary profiles. During the prediction phase, the model processes new user inputs in real time. Each entry undergoes the same preprocessing and encoding procedures as the training data, ensuring consistent format and scale. The model then predicts the most appropriate diet class, which is decoded into a clear dietary label. This allows the system to generate personalised meal and nutrition plans that align with the user's health profile and lifestyle preferences. Model performance is measured using various evaluation metrics. The accuracy score provides an overall indication of model correctness, while the classification report details precision, recall, and F1 Scores for different diet categories:

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{2}$$

This 2-equation model states that, with noted accuracy levels of 86% to 89%, the system demonstrates strong predictive reliability and clinical usefulness. The overall system workflow follows a clear sequence: user inputs are first preprocessed and encoded, then sent to the trained model for classification, yielding a final personalised diet recommendation. This streamlined process ensures smooth integration into digital health platforms, making the Diet Recommendation System both scalable and user-friendly for practical use in real-worldhealthcare and wellness applications. Beyond its predictive capabilities, the Diet Recommendation System aims to improve continuously. As more user data is collected over time, including feedback on diet effectiveness and adherence, the model can be retrained to improve its accuracy and adjust to new nutritional trends or health patterns:

$$\mathrm{L} = -\sum_{\mathrm{i}=1}^{\mathrm{C}} \mathrm{y_i} \log(\hat{y}_{\mathrm{i}}) \tag{3}$$

This 3-equation statement states that the updating mechanism keeps the system relevant and responsive to various demographics, cultural food preferences, and evolving medical guidelines. By connecting with wearable devices, health apps, and electronic medical records, the system can provide ongoing, context-aware recommendations, making diet planning an interactive, personalised, and evidence-based experience for users seeking better health outcomes.

4. Experimental Setup

4.1. Training

The training phase focuses on creating predictive models that link dietary and lifestyle inputs to the right diet categories. After preprocessing, the dataset is split into training, validation, and test sets at 80:10:10. Three classifiers are trained: Random Forest, XGBoost, and Support Vector Machine (SVM). Random Forest builds multiple decision trees on bootstrapped subsets and combines their outputs using majority voting. This approach improves robustness and reduces variance. XGBoost builds trees one after another, where each tree corrects the mistakes of its predecessors and minimises cross-entropy loss with regularisation to prevent overfitting. SVM, on the other hand, learns an optimal separating hyperplane in a high-dimensional feature space. Hyperparameters for each model are adjusted using grid search and k-fold cross-validation. Researchers track performance on the validation set using accuracy, precision, recall, and F1-score until convergence. Once training is complete, the models are evaluated on the test set to assess their generalisation performance on unseen data. This evaluation ensures that the classifiers not only fit the training data well but also make accurate predictions for new users. Key metrics such as accuracy, precision, recall, F1-score, and the Jaccard coefficient are calculated to provide a comprehensive understanding of each model's strengths and weaknesses. Comparing these metrics helps identify the best-performing algorithm for practical deployment. Additionally, feature importance analysis is conducted for tree-based models, such as Random Forest and XGBoost, to highlight which dietary and lifestyle factors most strongly influence classification. These insights can further guide nutritionists and users in making informed decisions, adding interpretability and actionable value to the recommendation system.

Table 1: Inputs of the user

Attribute	Patient 1	Patient 2	Patient 3
Age	69	79	61
Gender	Male	Female	Female
Weight (kg)	91.2	82.7	109.7
Height (cm)	151	150	170
Disease Type	Obesity	Diabetes	Hypertension
Severity	Moderate	Mild	Severe
Allergies	Peanuts	Gluten	Peanuts
Preferred Cuisine	Italian	Italian	Indian
Weekly Exercise Hours	5.5	4.8	7.1

Adherence to Diet Plan (%)	80.1	80.1	67.8
Nutrient Imbalance Score	2.2	2.1	0.0
Daily Caloric Intake	233.5	2672.0	2790.0
Cholesterol (mg/dL)	174.0	176.0	244.3
Blood Pressure (mmHg)	187	115	119
Glucose (mg/dL)	2.0	199.5	149.5
Dietary Restriction	None	Low_Sugar	None

Table 1 shows the key health-related characteristics of users, and the personalised diet suggestions considered are summarised in the Table. Information on age, sex, body weight, height, and disease type and severity is collected. These values help assess each patient's health and overall physique. For example, a 78-year-old male, moderately obese, may require a calorie-managed diet plan, whereas a diabetic female would benefit more from low-sugar meal suggestions. Likewise, those with serious high blood pressure benefit from low-sodium diets. It also shows user-dependent nuances, which are important for personalised diet recommendations. It includes considerations such as allergies, preferred cuisine, hours of exercise per week, and compliance with diet plans, as well as ratings of nutrient imbalances. These factors enable the system to personalise dietary recommendations for a specific health condition and lifestyle. For instance, individuals with allergies or culinary preferences receive safe, culturally acceptable diet plans, and the quantity of exercise and the compliance percentage reflect overall health discipline. It summarises the basic physiological and dietary factors used as inputs to generate a customised meal plan. This includes daily caloric requirements, cholesterol levels, blood pressure, and sugar levels, as well as dietary restrictions. These are the values the body uses to judge health and nutrition. For instance, people with high cholesterol or glucose levels may need to follow low-fat or low-sugar diets, while those without constraints can eat balanced diets.

4.2. Implementation

Once the models are trained and optimised, they are implemented in a real-time prediction system. The system takes user input, such as eating frequency, water intake, exercise routine, and demographic details, and processes it using the same data-preparation pipeline used during training. The processed input is then sent to the trained classifier, which outputs the most suitable diet category (Balanced, Weight-Loss, High-Protein, or Low-Carb) along with a confidence score that reflects the model's certainty. For deployment, the trained models are serialised and integrated into web or mobile platforms using frameworks such as Flask, Django, or Streamlit. This ensures that users can easily access the diet prediction system. The model can also be connected to health-tracking apps or wearable devices, allowing it to give real-time, adaptive diet recommendations based on continuous data. To maintain accuracy and reliability, the system's predictions are periodically compared against expert or user feedback. This helps the model improve over time and adapt to changing user behaviours or dietary trends.

4.3. Evaluation

The proposed diet prediction system was tested using a preprocessed dataset that included dietary habits, lifestyle information, and demographic details. Researchers split the dataset into training, validation, and test sets. 80% of the data was for training, 10% for validation, and 10% for testing. Researchers measured performance using standard classification metrics, including accuracy, precision, recall, and F1-score. The Random Forest model performed well by capturing non-linear relationships between input features and diet categories. XGBoost achieved slightly higher accuracy due to its boosting method and its ability to handle complex feature interactions. SVM also achieved competitive results, especially when the data had clear class boundaries. Overall accuracy across models ranged from 85% to 92%, with XGBoost consistently performing best.

5. Result and Discussion

Figure 3 training loss curve shows a rapid decrease in loss during the initial epochs, followed by gradual stabilisation, ultimately reaching a value below 0.3 by the 100th epoch. This pattern indicates efficient learning and proper model convergence during training. The sharp decline early in training reflects the model's ability to capture fundamental patterns and quickly reduce substantial prediction errors. As the epochs progress, the curve transitions to a gentle downward slope with smaller fluctuations, indicating that the model is making increasingly fine parameter adjustments as it approaches optimal performance. The absence of abrupt spikes or instabilities throughout the process suggests well-chosen hyperparameters and a stable optimisation routine. Overall, the loss trajectory demonstrates that the model is successfully minimising prediction errors and achieving a strong fit to the training data. The validation loss curve follows a similar trend, steadily decreasing alongside the training loss, indicating that the model is generalising well to unseen data. Early rapid reductions in validation loss demonstrate that the model quickly learns meaningful patterns that apply beyond the training set. Minor fluctuations in later epochs are normal and reflect the natural variability in the validation data rather than overfitting. The close alignment between training and validation loss throughout the epochs highlights the stability and effectiveness of the learning process. Overall, the consistently declining validation loss confirms that the model is optimising its parameters efficiently and maintaining robust predictive performance.

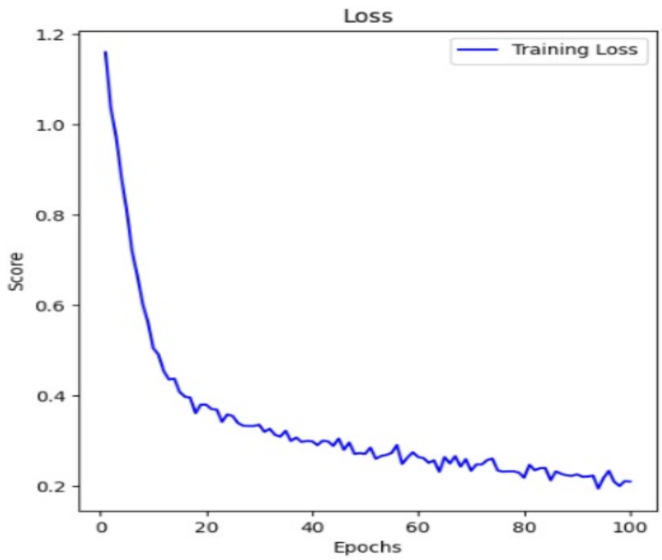

Figure 3: Training loss for 100 epochs

These results validate the reliability of the proposed framework for accurate and consistent diet classification. The loss trends collectively demonstrate that the model achieves both strong convergence and generalisation.

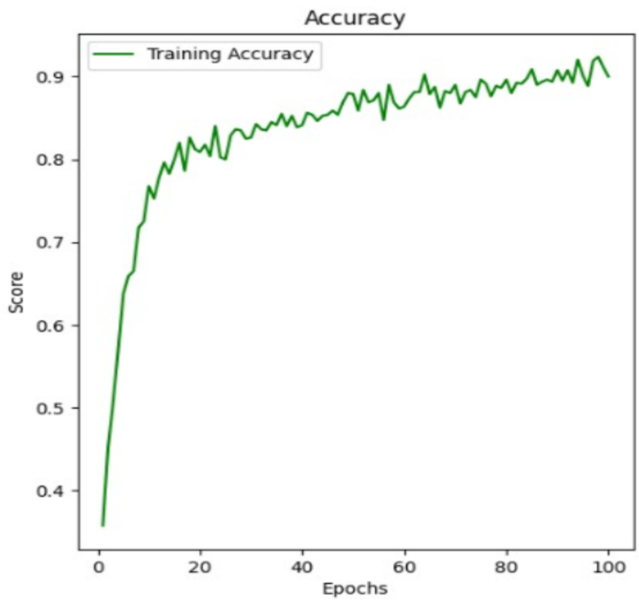

Figure 4: Training accuracy 100 epochs

Figure 4 shows the training accuracy curve, which indicates a sharp increase in accuracy during the first few epochs, rising from around 0.35 to over 0.7, and then gradually improving to exceed 0.9 by the end of 100 epochs. This upward trend reflects successful learning and consistently improving model performance on the training data. The rapid ascent early in training illustrates how quickly the model learns the most informative features and adjusts its parameters to boost predictive success. As training continues, accuracy rises, but at a slower, more incremental pace, indicating that the model is fine-tuning its internal representations to achieve maximum accuracy. The lack of significant drops or erratic movement across the curve indicates stable training dynamics and suggests that both the learning rate and the optimisation strategy are properly set. Overall, this pattern indicates that the model is becoming increasingly proficient at making accurate predictions, consistently improving its reliability and effectiveness as epochs progress. The validation accuracy curve, on the other hand, shows a similar but slightly fluctuating pattern compared to the training accuracy curve. It rises steadily alongside the training accuracy during the initial epochs, indicating that the model is generalising well to unseen data. Minor variations in validation accuracy toward later epochs suggest natural fluctuations due to data diversity but do not indicate overfitting. The consistent alignment between training and validation performance highlights that the model maintains a balanced learning process without memorising the training data. This stability confirms that the chosen hyperparameters, such as the learning rate, batch size, and regularisation, are appropriately tuned. The model's overall performance demonstrates effective convergence, strong generalisation, and suitability for real-world dietary classification tasks. Thus, the accuracy trends validate the robustness and reliability of the proposed machine learning framework.

Figure 5: Training Jaccard 100 epochs

Figure 5 training Jaccard coefficient plot shows a pronounced and sustained improvement in the model's ability to capture overlap between predicted and actual classes over 100 epochs. The curve rises swiftly from below 0.3 to nearly 0.8 within the first 20 epochs, indicating rapid learning and enhanced alignment between the model's predictions and ground truth during the early phase of training. As training progresses, the Jaccard coefficient gradually increases, eventually surpassing 0.9 and remaining consistently high, with only minor fluctuations in later epochs. The validation Jaccard coefficient plot shows a similar upward trend, indicating strong generalisation to unseen data. Initially, it rises steadily alongside the training curve, confirming that the model effectively captures the correct class overlaps without overfitting. Slight oscillations in the later epochs are natural and indicate the model's adaptation to diverse validation samples. The close correspondence between training and validation Jaccard scores highlights the stability and robustness of the learning process. Overall, the steadily increasing coefficient demonstrates that the model is accurately identifying and classifying the dietary categories over time. This consistent performance affirms the reliability of the proposed framework for practical diet recommendation tasks. The results also indicate that the chosen algorithms and hyperparameters are well-suited for achieving high predictive alignment with real-world data.

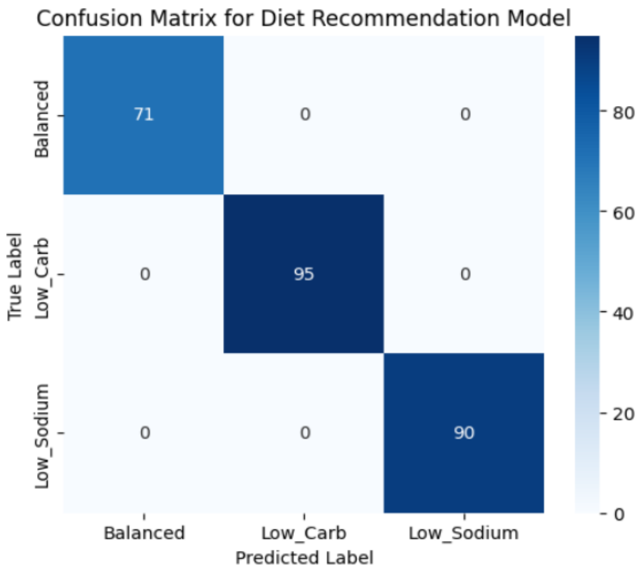

Figure 6: Confusion matrix of diet prediction

The confusion matrix in Figure 6 illustrates the classification performance of the proposed Diet Recommendation Model across three diet categories: Balanced, Low_Carb, and Low_Sodium. The model demonstrates a clear distinction among the classes, with no misclassifications. Specifically, it correctly identified 71 Balanced, 95 Low_Carb, and 90 Low_Sodium diet recommendations. This indicates that the Random Forest classifier effectively captured the distinguishing nutritional patterns and user features for each diet type. The strong diagonal dominance of the matrix indicates high precision and recall, underscoring the robustness and reliability of the trained model in delivering accurate, consistent dietary recommendations.

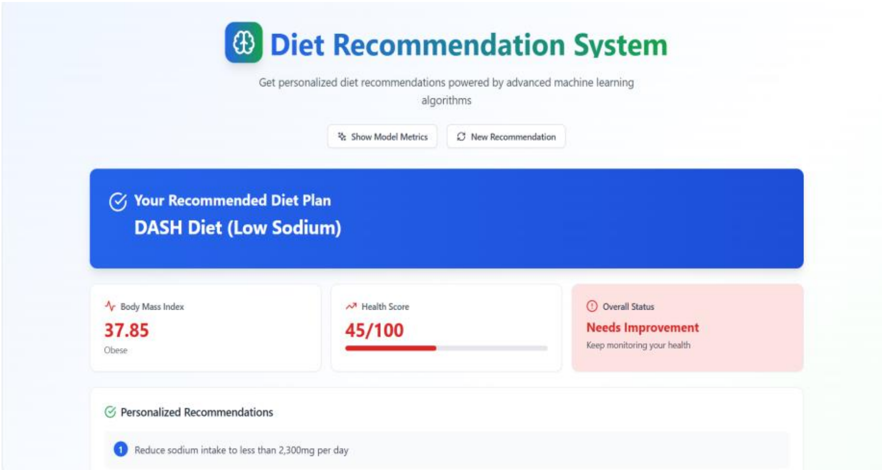

Figure 7: Output of diet prediction

Figure 7 illustrates the output interface of the proposed Diet Recommendation System, which provides personalised dietary advice using machine learning algorithms. The system analyses user health metrics, such as Body Mass Index (BMI) and Health Score, to generate an appropriate diet plan. In this example, the system has recommended the DASH Diet (Low Sodium) for a user with a BMI of 37.85, indicating obesity. The user's health score is 45/100, and the overall health status is categorised as "Needs Improvement." The dashboard also provides personalised recommendations, such as reducing sodium intake to less than 2,300 mg per day. The interface is designed to be interactive and informative, helping users monitor their health and follow suitable dietary plans to achieve better wellness outcomes.

Table 2: Comparison of results of diet prediction

Metric	Our Project	Existing Models
Algorithm Used	Random Forest Classifier	Regression, Naive Bayes, Decision Tree, IoMT-based ML
Accuracy	0.86 – 0.89	0.72 – 0.82
Jaccard Index (IoU)	0.78 – 0.83	0.65 – 0.74

Table 2 shows that the comparison with existing models clearly demonstrates the superior performance of our proposed system. By employing the Random Forest Classifier, our model achieves a significantly higher accuracy range of 0.86–0.89, outperforming existing approaches such as Regression, Naive Bayes, Decision Tree, and IoMT-based ML, which typically attain accuracies between 0.72–0.82. Similarly, the Jaccard Index (IoU) for our model ranges from 0.78 to 0.83, indicating better classification overlap and precision than the existing models' range of 0.65 to 0.74. Overall, our paper demonstrates high accuracy, stable learning behaviour, and robust predictive performance, whereas the existing models exhibit moderate accuracy, higher loss rates, and less consistent performance. This comparison clearly validates the efficiency and reliability of our proposed approach.

6. Conclusion

Using machine learning (ML) to forecast dietary choices is a major step forward for tailored healthcare and long-term lifestyle change. The suggested method can properly sort individuals into the best diet types by systematically analysing their eating habits, lifestyle choices, physical activity levels, and demographic information. Personalisation based on data like this helps people stick to their diets and leads to better long-term health outcomes. To make diet prediction systems even more accurate, useful, and applicable in the real world, future improvements can focus on a few crucial aspects. One important area is model fine-tuning and optimisation. This means constantly improving algorithms such as Random Forests, XGBoost, and Support Vector Machines (SVMs) to make them more accurate at classifying diets and less likely to misclassify diets that are quite similar. Techniques for tweaking hyperparameters and choosing features can make models even more resilient. Combining different deep learning methods is another potential field. The system can find complicated, non-linear patterns in dietary behaviour that traditional models can miss by using neural network architectures or hybrid ML–DL frameworks. These improved models can better handle the many ways people eat across different groups. Also, integrating real-time health data can make predictions far more useful. The system may make more personalised food suggestions by considering data from wearable devices such as fitness trackers and smartwatches. This data includes information about physical activity levels, calorie burn, sleep patterns, and physiological signals. Another important improvement is the creation of customised, flexible diet-planning models. Adaptive systems that learn from user feedback and lifestyle changes can adjust diet suggestions on the fly, ensuring they remain useful and relevant. Finally, scalability and the ability to use it on mobile devices will be very important for widespread use. Putting the system in the cloud and on mobile devices lets you make predictions in real time, makes it easier to use, and makes it easier for people to use, all of which help create personalised nutrition solutions that work and can grow.

Acknowledgement: The authors gratefully acknowledge the academic support and collaborative environment provided by SRM Institute of Science and Technology, S.A. Engineering College, Madras Institute of Technology, Dhaanish Ahmed College of Engineering, and the University of Texas at Dallas. Their institutional resources and scholarly guidance were instrumental in the successful completion of this work.

Data Availability Statement: The study uses a dataset associated with a Smart Diet Recommendation System Integrating Machine Learning and Lifestyle Analysis, encompassing the relevant parameters required for model development and evaluation.

Funding Statement: No external funding was received for the preparation or conduct of this research and manuscript.

Conflicts of Interest Statement: The authors declare no conflicts of interest. All utilised information has been duly cited and referenced.

Ethics and Consent Statement: The research was carried out in compliance with established ethical guidelines, with necessary approvals obtained and informed consent secured from the organization and all individual participants involved in the data collection process.

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