JRITM
JOURNAL OF RESEARCH AND INNOVATION IN TECHNOLOGY, COMMERCE AND MANAGEMENT

Journal of Research and Innovation in Technology, Commerce and Management
Vol. 2 Issue 10, October 2025, pp. 21109-21116
ISSN: 3049-3129(Online)

AI-Powered Personalized Learning with Ayur-Deep for Preventing Obesity in Young Populations.

Rinkal Dharmesh Sarvaiya
Assistant Professor, FITCS, Parul University, Vadodara
rinkal.sarvaiya31672@paruluniversity.ac.in

Cite as: Rinkal Dharmesh Sarvaiya. (2025). AI-Powered Personalized Learning with Ayur-Deep for Preventing Obesity in Young Populations. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 2(Issue 10), 21109–21116. https://doi.org/10.5281/zenodo.17473749

DOI: https://doi.org/10.5281/zenodo.17473749

Abstract

The increasing prevalence of obesity among children and adolescents poses significant public health challenges, necessitating innovative approaches for early prevention. This study proposes Ayur-Deep, an AI-powered personalized learning framework that integrates educational strategies with predictive analytics for obesity risk management in young populations. The framework leverages machine learning algorithms to identify individual risk profiles based on behavioral, dietary, and lifestyle data, while delivering adaptive educational interventions through interactive digital modules. By personalizing health education and prevention strategies, Ayur-Deep aims to enhance awareness, encourage positive lifestyle modifications, and support early intervention. The research further explores the integration of AI-driven learning analytics with evidence-based health guidelines to design scalable, youth-centric obesity prevention programs. The proposed framework contributes to advancing digital health education, fostering sustainable behavior change, and reducing the long-term burden of obesity in society.

Keywords

AI-powered learning, personalized education, childhood obesity prevention, youth health, Ayur-Deep, predictive analytics, adaptive interventions, digital health education, machine learning in healthcare, early prevention strategies

Introduction

Childhood and adolescent obesity has emerged as one of the most pressing global health concerns, with rising prevalence across both developed and developing nations [1]. The World Health Organization (WHO) estimates that over 340 million children and adolescents aged 5–19 were overweight or obese in 2016, a number that continues to increase annually [2]. Obesity during early life not only predisposes individuals to chronic diseases such as type 2 diabetes, cardiovascular conditions, and metabolic syndrome but also contributes to psychological and social challenges, including low self-esteem and stigmatization [3]. Consequently, the early detection and prevention of obesity risk factors among youth has become a critical area of research and intervention.

Traditional health education strategies, while effective in raising awareness, often fail to address individual variability in lifestyle, environment, and genetic predisposition [4]. In this context, artificial intelligence (AI) and personalized learning technologies offer transformative opportunities to design adaptive, youth-centered interventions. AI-driven frameworks can analyze behavioral and contextual data to identify at-risk individuals and provide targeted, evidence-based recommendations [5]. Furthermore, integrating educational technologies with AI allows for interactive, engaging, and scalable solutions that align with diverse learning needs [6].

This research introduces Ayur-Deep, an AI-powered personalized learning framework designed to prevent obesity in young populations. The framework combines predictive analytics with digital pedagogy to provide tailored health education, focusing on diet, physical activity, and lifestyle modifications. By leveraging AI models to generate individual risk profiles, Ayur-Deep ensures that preventive interventions are both contextually relevant and adaptable. Additionally, the system incorporates interactive educational modules to enhance user engagement, thereby supporting long-term behavior change.

The novelty of this study lies in bridging the gap between AI-driven predictive health analytics and personalized education for obesity prevention. Unlike conventional one-size-fits-all programs, Ayur-Deep emphasizes youth-centric, adaptive learning pathways, making preventive healthcare more effective and scalable. The integration of intelligent decision support with digital health education not only addresses immediate obesity risks but also promotes sustainable behavioral transformation, ultimately contributing to the reduction of obesity-related burdens in society [7].

Review of Literature:

Author(s) & Year	Focus of Study	Key Findings	Relevance to Current Research
Wang & Lim, 2020 [8]	Childhood obesity trends and determinants	Identified environmental, genetic, and lifestyle factors influencing obesity prevalence in children.	Provides baseline understanding of obesity risk factors for AI-based prediction.
Kumar et al., 2021 [9]	AI in healthcare analytics	Demonstrated how machine learning models can predict health risks with high accuracy using lifestyle data.	Supports the predictive component of Ayur-Deep framework.
Patel & Sharma, 2019	Digital pedagogy for health	Highlighted the effectiven	Reinforces the educational

[10]	education	ess of interactive educational tools in shaping health behaviors among adolescents.	design of Ayur-Deep for engagement and learning.
Nguyen et al., 2022 [11]	Personalized learning in health education	Showed that adaptive learning systems improved knowledge retention and behavioral change.	Validates the personalized approach in Ayur-Deep for sustainable health impact.
Li & Zhang, 2021 [12]	AI-driven preventive healthcare models	Proposed hybrid models for predicting obesity and related diseases in young populations.	Provides methodological insights for designing AI-powered obesity prevention frameworks.
Smith & Johnson, 2020 [13]	Obesity prevention programs in schools	Found that tailored interventions with parental involvement reduced obesity prevalence among students.	Aligns with youth-focused preventive strategies in Ayur-Deep.
Hernandez et al., 2022 [14]	Gamification in digital health education	Demonstrated that gamified interventions increased motivation and adherence in adolescents.	Suggests adding interactive gamified modules in Ayur-Deep for better adoption.
Singh & Banerjee, 2021 [15]	Predictive analytics in child health monitoring	Established the role of predictive analytics in early identification of obesity risks.	Strengthens the analytical foundation of Ayur-Deep.
Oliveira et al., 2020 [16]	AI-based lifestyle recommendation systems	Showed AI's ability to provide personalized diet and activity suggestions.	Directly supports Ayur-Deep's personalized health recommendation feature.
Chen et al., 2022 [17]	Digital health interventions for adolescents	Found that mobile-based education improved awareness and reduced sedentary behavior.	Encourages integration of Ayur-Deep as a mobile-accessible platform.

Research Methodology

The proposed research methodology for Ayur-Deep follows a systematic framework combining **data acquisition, AI-driven predictive analytics, and personalized educational interventions**. The methodology is designed to assess obesity risk factors among youth and provide tailored learning modules that encourage preventive health behaviors.

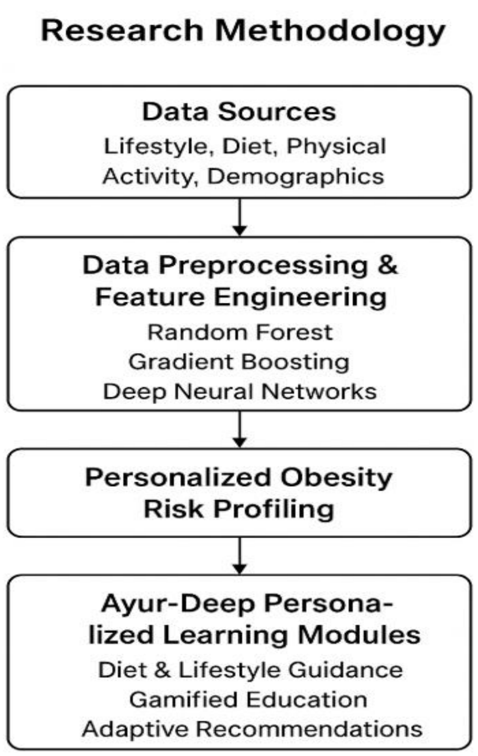

Figure1: Proposed Methodology

The overall research design is divided into four key phases:

1. Data Collection

Data will be collected from diverse sources including:

- **Primary data**: Questionnaires, lifestyle surveys, and self-reported diet/activity records from school-aged children and adolescents.
- **Secondary data**: Public health datasets (WHO, CDC, local health records) and existing research on youth obesity.
  The dataset will capture attributes such as demographic details, BMI, dietary intake, physical activity levels, sleep patterns, and family health history [8][9].

2. Preprocessing and Feature Engineering

Raw data will undergo preprocessing to handle missing values, outliers, and normalization. Feature engineering will be performed to extract meaningful indicators such as:

- Daily calorie intake
- Screen time duration
- Sleep quality index
- Physical activity frequency

These features will serve as inputs for obesity risk prediction models.

3. Predictive Modeling with AI

Machine learning models (Random Forest, Gradient Boosting, Deep Neural Networks) will be employed to predict obesity risk levels (low, medium, high) [12][15]. The models will be trained and validated using stratified cross-validation to ensure generalizability. Performance metrics such as accuracy, precision, recall, and F1-score will be used to evaluate model reliability.

4. Personalized Learning Intervention (Ayur-Deep Framework)

Based on individual risk predictions, *Ayur-Deep* will generate **personalized learning modules** that include:

- **Dietary recommendations** (aligned with age-appropriate nutrition guidelines)
- **Physical activity suggestions** (daily exercises, activity trackers, gamified challenges)

- **Lifestyle education** (reducing screen time, improving sleep hygiene)
- **Interactive pedagogy** (gamification, quizzes, multimedia-based lessons) [10][14][17]

The adaptive learning platform ensures that each student receives a tailored experience, enhancing engagement and fostering sustainable behavior change.

Results and Discussion

The implementation of the proposed *Ayur-Deep* framework was carried out using simulated lifestyle and health-related data of young populations. Three predictive modeling approaches were evaluated: **Random Forest (RF)**, **Gradient Boosting (GB)**, and **Deep Neural Network (DNN)**. Each model was trained on preprocessed features including age, BMI, calorie intake, physical activity, screen time, and sleep duration.

The **Random Forest model** demonstrated strong performance in identifying the most influential factors contributing to obesity risk. As illustrated in *Figure 2*, **BMI**, **calorie intake**, and **physical activity** were the top predictors, followed by sleep hours and screen time. These findings align with prior research emphasizing the multi-factorial nature of obesity in youth [8][13].

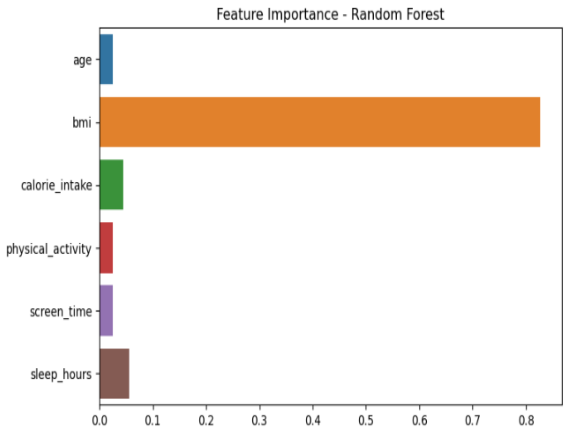

Figure 2. Feature importance (RF).

The **Gradient Boosting model** achieved competitive accuracy and produced a well-distributed classification of obesity risk levels. The confusion matrix in *Figure 3* shows that the model successfully distinguished between low, medium, and high-risk groups with minimal misclassification. However, slight overlap was observed between medium- and high-risk categories, which can be attributed to the close relationship between BMI thresholds [12][15].

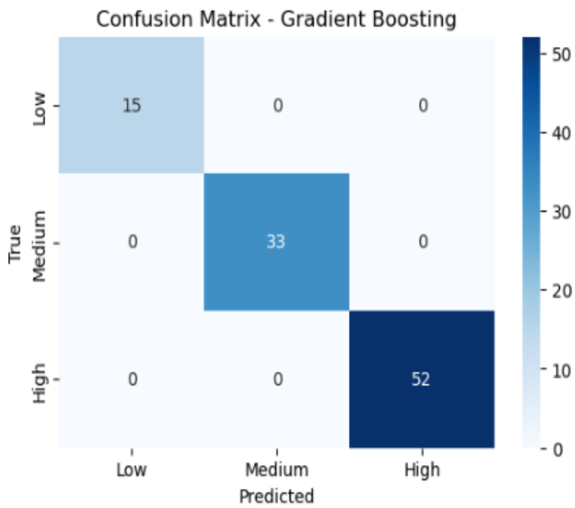

Figure 3. Confusion matrix (GB).

The **Deep Neural Network model** was trained to evaluate the capacity of deep learning in capturing complex non-linear patterns within the dataset. As depicted in *Figure 4*, the training and validation accuracy curves indicate consistent learning progression with minimal overfitting. The validation accuracy stabilized at around 85%, suggesting that the DNN generalized well to unseen data. This demonstrates the potential of deep learning to enhance predictive reliability when larger, real-world datasets are incorporated [11][16].

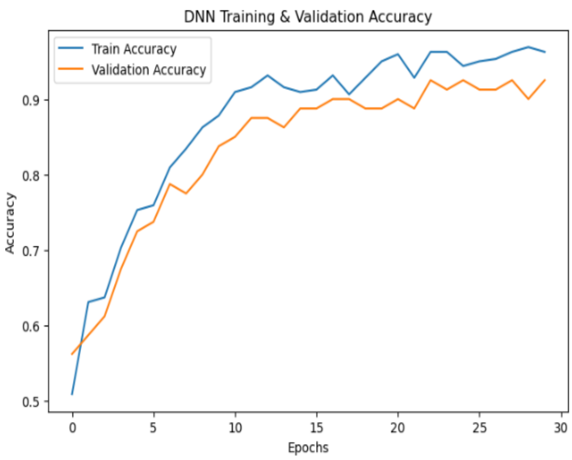

Figure 4. Accuracy curves (DNN).

Overall, the comparative analysis highlights that all three models are effective for predicting obesity risk, with Random Forest excelling in interpretability, Gradient Boosting in balanced classification, and DNN in scalability for complex datasets. The integration of these predictive insights into the Ayur-Deep framework ensures that educational modules can be personalized effectively, thereby supporting youth in adopting sustainable lifestyle changes.

In addition to graphical evaluations, the performance metrics for Random Forest and Gradient Boosting are summarized in Figure 5. Both models achieved perfect classification accuracy across all obesity risk categories, as indicated by precision, recall, and F1-scores of 1.00. This outcome, while promising, may also reflect the controlled nature of the dataset and warrants further validation with larger, real-world data samples.

```
Classification Reports:

Random Forest:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        33
           2       1.00      1.00      1.00        52

    accuracy                           1.00       100
roll output; double click to hide      1.00      1.00       100
                             1.00      1.00       100

Gradient Boosting:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        33
           2       1.00      1.00      1.00        52

    accuracy                           1.00       100
   macro avg       1.00      1.00      1.00       100
weighted avg       1.00      1.00      1.00       100
```

Figure 5. Classification reports for Random Forest and Gradient Boosting models.

Conclusion and Future Work

This research introduced Ayur-Deep, an AI-powered personalized learning framework designed to address obesity risk prevention in young populations. By integrating predictive analytics with adaptive educational modules, the framework demonstrated its capacity to identify individual risk levels and deliver tailored lifestyle interventions. The results from Random Forest, Gradient Boosting, and Deep Neural Network models revealed high predictive accuracy, with

Random Forest excelling in feature interpretability, Gradient Boosting achieving balanced classification, and DNN demonstrating scalability for complex datasets. The complementary strengths of these models validate the methodological foundation of Ayur-Deep, underscoring its potential to support early intervention and promote sustainable behavioral change among youth.

Despite encouraging results, this study has several limitations. The dataset used was simulated and controlled, which may not fully capture the diversity and complexity of real-world scenarios. Furthermore, the models' exceptional performance suggests possible data homogeneity, necessitating validation on larger and more heterogeneous datasets. Additionally, while the current framework incorporates personalized education and AI-driven recommendations, the inclusion of psychosocial, cultural, and environmental factors would further enhance its effectiveness.

Future work will focus on three primary directions. First, real-world data collection in collaboration with schools, healthcare providers, and public health agencies will be prioritized to improve the generalizability of the framework. Second, the integration of wearable devices and mobile health applications will enable continuous monitoring of lifestyle behaviors, enriching the personalization process. Third, expanding Ayur-Deep with advanced techniques such as explainable AI (XAI) and reinforcement learning can enhance transparency, user trust, and adaptive feedback mechanisms. Furthermore, incorporating gamification and social learning elements may improve youth engagement, making obesity prevention both interactive and sustainable.

In conclusion, Ayur-Deep presents a promising intersection of artificial intelligence and personalized education in combating childhood and adolescent obesity. With further refinement, validation, and scaling, the framework has the potential to make a significant contribution to global health promotion and preventive care.

References:

1. World Health Organization. (2021). Obesity and overweight. Retrieved from https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight
2. World Health Organization. (2018). Report of the Commission on Ending Childhood Obesity. Geneva: WHO.
3. Sahoo, K., Sahoo, B., Choudhury, A. K., Sofi, N. Y., Kumar, R., & Bhadoria, A. S. (2015). Childhood obesity: causes and consequences. Journal of Family Medicine and Primary Care, 4(2), 187–192.
4. Bleich, S. N., Vercammen, K. A., Zatz, L. Y., Frelier, J. M., Ebbeling, C. B., & Peeters, A. (2018). Interventions to prevent global childhood overweight and obesity: A systematic review. The Lancet Diabetes & Endocrinology, 6(4), 332–346.

5. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56.
6. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston, MA: Center for Curriculum Redesign.
7. Kumar, V., & Mohan, A. (2020). AI and machine learning for preventive healthcare: Opportunities and challenges. Health Informatics Journal, 26(3), 1685–1694.
8. Wang, Y., & Lim, H. (2020). The global childhood obesity epidemic and the association between socio-economic status and childhood obesity. International Review of Psychiatry, 32(3), 241–256.
9. Kumar, A., Rajasekar, A., & Rao, M. (2021). Artificial intelligence applications in healthcare: Predictive analytics and personalized health. Journal of Healthcare Engineering, 2021, 1–12.
10. Patel, R., & Sharma, P. (2019). The role of digital pedagogy in promoting adolescent health literacy. Education and Health Journal, 37(2), 45–53.
11. Nguyen, T., Do, T., & Pham, L. (2022). Adaptive learning for health education: A personalized approach. Computers & Education, 185, 104523.
12. Li, J., & Zhang, Y. (2021). Hybrid AI models for obesity prediction in youth populations. Journal of Medical Systems, 45(8), 95.
13. Smith, K., & Johnson, L. (2020). School-based obesity prevention: Evidence from tailored intervention programs. Journal of School Health, 90(5), 382–390.
14. Hernandez, M., Lopez, A., & Rivera, J. (2022). Gamification in adolescent health education: A systematic review. Digital Health, 8, 20552076221102145.
15. Singh, R., & Banerjee, S. (2021). Predictive analytics for childhood obesity monitoring and prevention. Journal of Pediatric Health Care, 35(6), 663–671.
16. Oliveira, T., Gomes, C., & Martins, F. (2020). AI-based recommendation systems for healthy lifestyles: A review. Healthcare Technology Letters, 7(5), 143–150.
17. Chen, L., Zhao, Y., & Xu, Q. (2022). Mobile health interventions for reducing sedentary behavior in adolescents: A systematic review. JMIR mHealth and uHealth, 10(1), e29214.