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Full Length Article

Predicting Adolescent Concern Toward Unhealthy Food Advertisements Using Deep Neural Networks With Explainable AI

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ABSTRACT:
Predicting adolescent concern over unhealthy food advertisements is critical for promoting health awareness and guiding public policy. This study utilizes XGBoost, a gradient boosting machine learning model, to predict concern levels among adolescents based on demographic and behavioral features. Survey data from 1030 adolescents were collected, including age, parental education, and advertisement exposure types, such as celebrity endorsements and free toys. The model is trained with hyperparameter tuning and synthetic oversampling to handle imbalanced classes. Explainable AI techniques (LIME and SHAP) are applied to interpret feature importance, providing insights into which factors most influence adolescent concern. Results demonstrate that XGBoost achieves high predictive accuracy, offering an effective and interpretable solution for understanding and mitigating the impact of unhealthy food advertisements.

***Keywords**: XGBoost, Explainable AI, Adolescent Health, LIME, SHAP, Machine Learning, Food Advertisements.*

INTRODUCTION

Unhealthy food advertisements are a significant concern, particularly for adolescents, who are highly impressionable and vulnerable to advertising tactics. These advertisements often promote foods high in sugar, fat, and salt, contributing to the growing prevalence of childhood obesity and other health-related issues. Adolescents are particularly at risk due to their developing cognitive and emotional stages, making it crucial to understand the factors influencing their concern or indifference towards such advertisements. By predicting adolescent concern, public health campaigns and policy interventions can be more effectively tailored to counteract the negative impact of unhealthy food advertisements.

By incorporating demographic and behavioral features such as age, parental education, and advertisement exposure types this research aims to predict adolescents levels of concern toward unhealthy food advertisements. Understanding the drivers behind these concerns is key to designing targeted interventions that can reduce the influence of such advertisements on adolescents.

Explainable AI techniques, such as LIME and SHAP, are integrated into this study to provide transparency and interpretability of the model's decisions.These methods help unravel the underlying factors influencing adolescent's concerns about unhealthy food advertisements. By explaining the model's predictions, stakeholders from policymakers to marketers gain insights into which features, such as celebrity endorsements or free toys, have the most significant impact on concern. This approach offers not only accurate predictions but also valuable insights into how advertisement-related features affect adolescent perceptions, leading to more informed decision-making in health policy and marketing strategies.

SCOPE OF THE PAPER

The scope of this project is focused on predicting adolescent concern toward unhealthy food advertisements using machine learning techniques, specifically deep neural networks and XGBoost. The study analyzes a dataset consisting of demographic and behavioral features, such as age, parental education, and exposure to various types of advertisements, including celebrity endorsements and promotional offers like free toys.

Additionally, the application of explainable AI methods like LIME and SHAP allows for the interpretation of feature importance, offering insights into the factors that influence adolescents concern. The findings from this study aim to support

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targeted health interventions and inform policies designed to mitigate the effects of unhealthy food advertisements on adolescents.

EXISTING SYSTEM:

The existing system utilizes a Stacking Ensemble approach combining Random Forest, K-Nearest Neighbors, and Support Vector Machines as base learners, with Logistic Regression as the meta-learner. The existing approach primarily relies on traditional ensemble learning without extensive integration of explainable AI methods. While Stacking Ensemble achieves high accuracy (~98.5%) and F1 scores (~0.99), understanding the influence of individual features such as age, parental education, and advertisement types requires additional analysis. Another limitation of the existing system is its dependency on carefully tuned base learners and meta-learner configuration. Any variation in data preprocessing or class imbalance can significantly affect performance. Furthermore, real-time prediction scenarios may be constrained due to computational overhead of multiple models operating in tandem.

PROPOSED SYSTEM

The proposed system implements XGBoost, a gradient boosting machine learning model, to predict adolescent concern levels regarding unhealthy food advertisements. Unlike the existing Stacking Ensemble, XGBoost provides efficient gradient-based optimization, reducing computational overhead while maintaining high predictive accuracy. The model leverages survey features such as age, parental education, and advertisement exposure types, including celebrity endorsements and free toys. Hyperparameter tuning and synthetic oversampling are applied to handle class imbalance, ensuring reliable predictions across low, medium, and high concern categories.

To enhance interpretability, the proposed system integrates Explainable AI techniques, including LIME and SHAP. These methods provide clear insights into feature importance, allowing stakeholders to understand which factors most influence adolescent concern. This explicit interpretability addresses limitations of the existing system, where feature effects were inferred indirectly. By combining high prediction performance with actionable insights, the proposed system supports data-driven decision-making for public health policies, advertising regulation, and educational campaigns aimed at improving adolescent dietary awareness.

The proposed system is highly scalable and adaptable to new data without requiring extensive retraining. XGBoost's gradient boosting approach ensures robustness against noise and variation in survey responses. Additionally, computational efficiency allows faster predictions compared to multi-model Stacking Ensembles. Overall, the integration of XGBoost with Explainable AI provides a practical, interpretable, and efficient solution for predicting adolescent concern over unhealthy food advertisements, bridging the gap between accurate predictive analytics and actionable understanding for policy and educational interventions.

LITERATURE SURVEY

Title: Consumer Behaviour to be Considered in Advertising: A Systematic Analysis and Future Agenda
Author: A. H. Alsharif, N. Z. M. Salleh, S. A. Al-Zahrani, and A. Khraiwish
Year: 2022

Description: This paper provides a comprehensive systematic analysis of consumer behavior in the context of advertising, emphasizing the importance of understanding consumer responses for effective marketing strategies. The study explores various psychological and emotional factors that influence consumer choices, particularly in response to food advertisements. By examining trends and patterns in consumer behavior, the authors propose a future research agenda to address gaps in current advertising practices. The research suggests that integrating consumer behavior insights with advertising strategies could enhance the effectiveness of marketing campaigns while promoting more responsible advertising practices, particularly for vulnerable populations like adolescents. This paper is crucial for understanding how consumer behavior insights can inform better-targeted advertising strategies.

Title: Effect of Food Marketing on Food Purchase Request, Eating Behaviour, and Dental Caries Amongst 5–8-Year-Old Children Belonging to Different Socioeconomic Backgrounds
Author: D. A. Mathur, D. A. Mathur, and D. Gopalakrishnan
Year: 2023

Description: This study examines the impact of food marketing on children's eating behavior, food purchase requests, and dental health, with a focus on children aged 5 to 8 years from diverse socioeconomic backgrounds. The research highlights the role of food advertising in shaping children's preferences for unhealthy food, which in turn influences their eating habits and overall health. Findings from this study underscore the need for greater regulation in food marketing targeted at

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children, as well as the importance of considering socioeconomic factors when assessing the influence of food advertisements. This paper contributes valuable insights for policymakers and public health officials working to mitigate the negative health outcomes linked to aggressive food marketing.

Title: Obesity in Children and Adolescents: Epidemiology, Causes, Assessment, and Management
Author: H. Jebeile, A. S. Kelly, G. O'Malley, and L. A. Baur
Year: 2022

Description: This paper provides an in-depth review of the growing obesity epidemic among children and adolescents, identifying the epidemiological factors, causes, and health implications. It outlines the significant role of environmental factors, including food advertising, in the development of obesity. The study discusses various assessment methods and management strategies for childhood obesity, with a focus on early intervention through policy changes and public health campaigns. The authors stress the need for comprehensive approaches that include regulating food marketing to children, promoting healthier eating habits, and increasing physical activity. This paper is highly relevant to understanding how external influences like advertisements contribute to obesity and how such issues can be addressed effectively.

METHODOLOGY

1. Data Collection and Preprocessing Module:
This module involves gathering data from various sources, including surveys and questionnaires distributed among adolescents. The collected dataset contains demographic and behavioral attributes such as age, parental education, and exposure to different types of advertisements. Once collected, the data undergoes preprocessing steps like handling missing values, removing duplicates, and converting categorical variables into numerical form suitable for machine learning.

2. Feature Extraction and Selection:
Feature extraction transforms raw data into meaningful variables, while feature selection helps remove redundant or irrelevant attributes that may affect the model's efficiency. Techniques such as correlation analysis and mutual information are applied to evaluate the importance of each feature.

3. Model Training (XGBoost):
In this module, the XGBoost algorithm is implemented to train the predictive model using the prepared dataset. XGBoost is a powerful gradient boosting technique known for its speed, scalability, and high accuracy. It works by sequentially building multiple decision trees and combining their results to improve prediction performance. During training, the algorithm minimizes classification errors by learning patterns from demographic and behavioral features that influence adolescent concern.

4. Hyperparameter Tuning:
Hyperparameters like learning rate, maximum depth, number of estimators, and subsample ratios significantly influence model accuracy and efficiency. Proper tuning prevents overfitting and underfitting, ensuring the model generalizes well to unseen data.

5. Class Imbalance Handling (Synthetic Oversampling):
In many real-world datasets, certain classes—such as highly concerned adolescents—may appear less frequently, leading to an imbalance. SMOTE generates synthetic samples of the minority class to balance the dataset, preventing the model from being biased toward the majority class. By creating a more evenly distributed dataset, the model can learn patterns from all concern levels more effectively. This process improves classification accuracy, fairness, and sensitivity in predicting less-represented categories, ensuring the final model performs well across diverse groups of adolescents with varying advertisement exposure.

6. Model Evaluation and Performance Metrics:
This module evaluates the trained XGBoost model using various performance metrics to assess its accuracy and reliability. Metrics such as accuracy, precision, recall, F1-score, and confusion matrix are used to measure how well the model predicts adolescent concern levels. The evaluation process helps identify potential weaknesses, such as overfitting or misclassification, and ensures that the model meets the required performance standards.

7. Insights and Visualization:
The final module focuses on interpreting and visualizing the model's results in a meaningful way. Charts, graphs, and visual reports are generated to display prediction trends, feature impacts, and overall model performance. Visualization helps stakeholders, researchers, and policymakers understand the findings intuitively, making complex data more accessible.

IMPLEMENTATION

The proposed system utilizes XGBoost, a gradient boosting machine learning algorithm, to predict adolescent concern levels over unhealthy food

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advertisements. It leverages survey-based input features including age, parental education, and exposure to specific advertisement types. XGBoost sequentially builds decision trees where each subsequent tree minimizes the residual errors of previous trees, ensuring high predictive accuracy while efficiently handling small and imbalanced datasets. Synthetic oversampling is applied to balance the classes, enhancing the model's reliability across low, medium, and high concern categories.

To make the model interpretable, Explainable AI techniques (LIME and SHAP) are integrated, enabling clear visualization of feature importance and contributions to each prediction. This allows stakeholders to understand how demographic and advertisement- related factors influence adolescent concern levels. The proposed algorithm not only achieves high accuracy but also provides actionable insights, bridging the gap between prediction performance and interpretability for educational campaigns and public health policy formulation.

ALGORITHM (XGBoost):

Input: Dataset containing age, parental education, and advertisement exposure types.

Preprocessing: Handle missing values, convert categorical data to numerical form, and perform data normalization.

Oversampling: Apply SMOTE to balance low, medium, and high concern categories.

Boosting: Sequentially build decision trees. Each new tree Tree_n is trained to predict the residuals (errors) of the combined model Tree_{n-1}.

Interpretability: Apply SHAP values to calculate the contribution of each feature to the final prediction.

BLOCK DIAGRAM

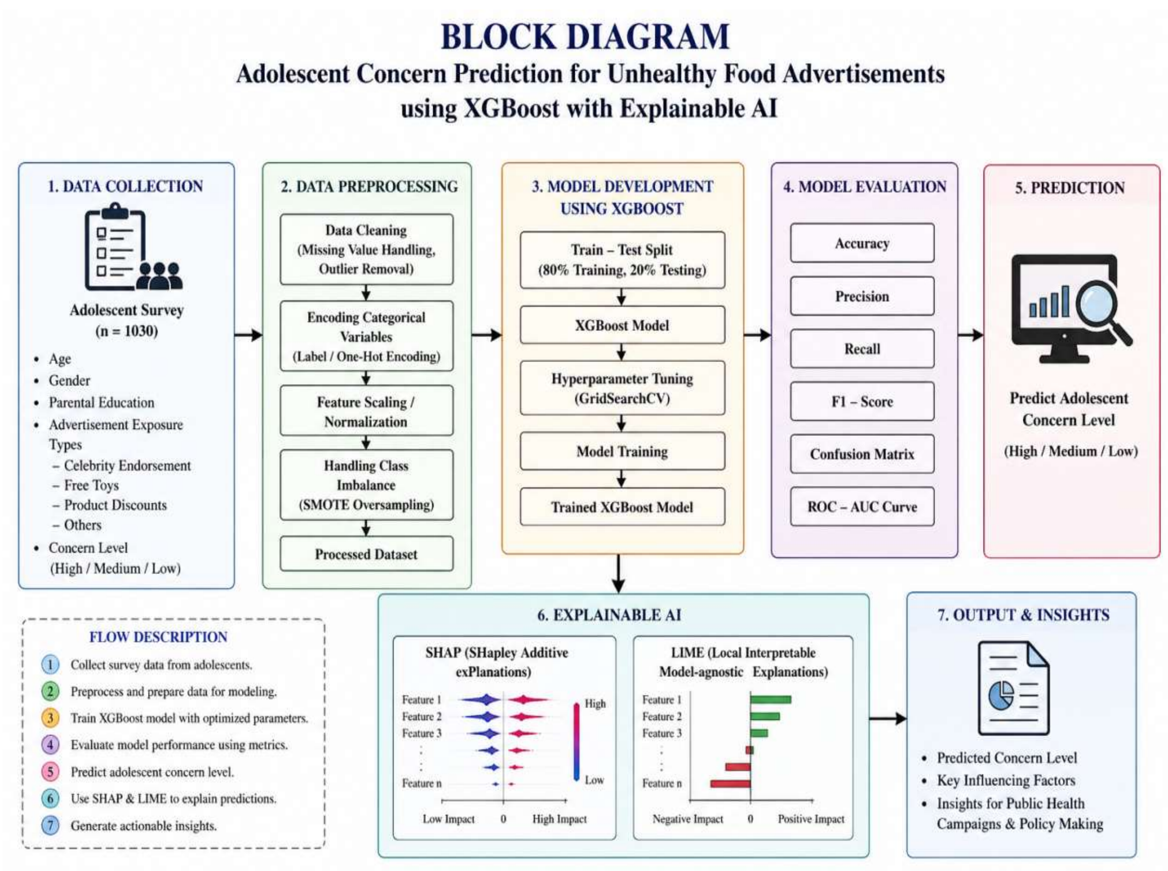

Fig 1. Block Diagram

SYSTEM ARCHITECTURE:

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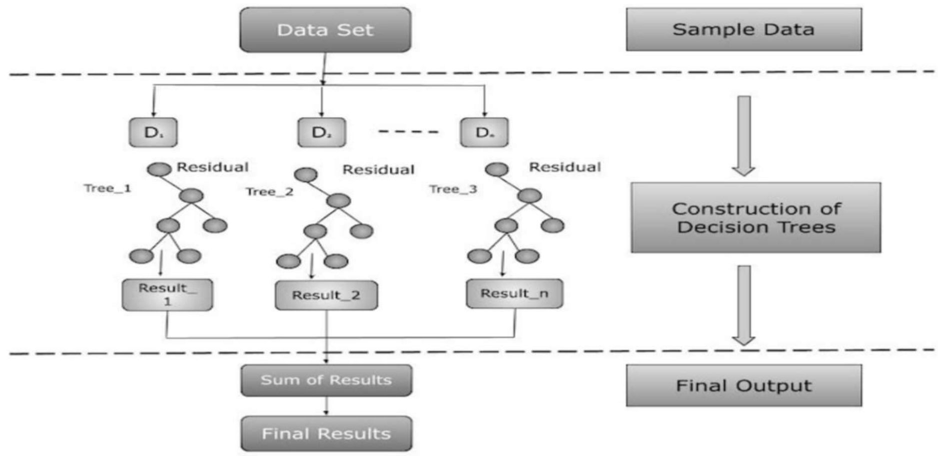
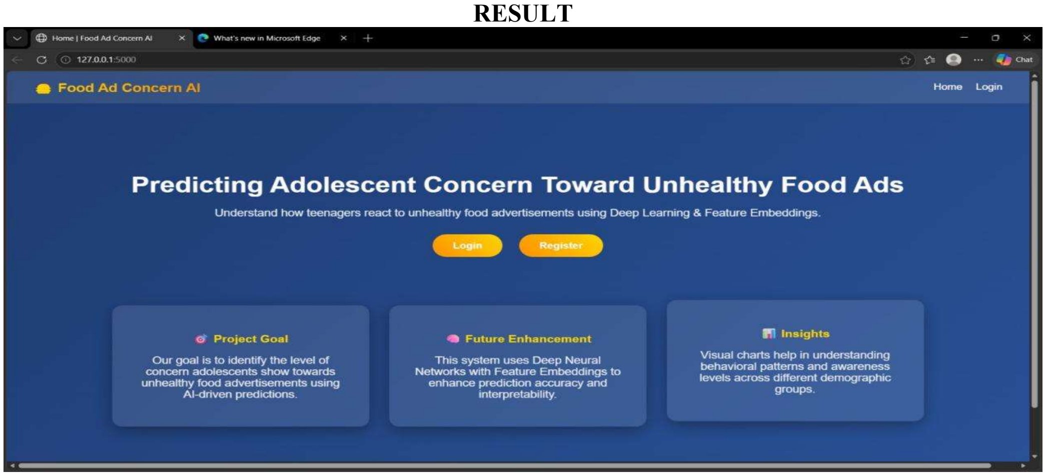
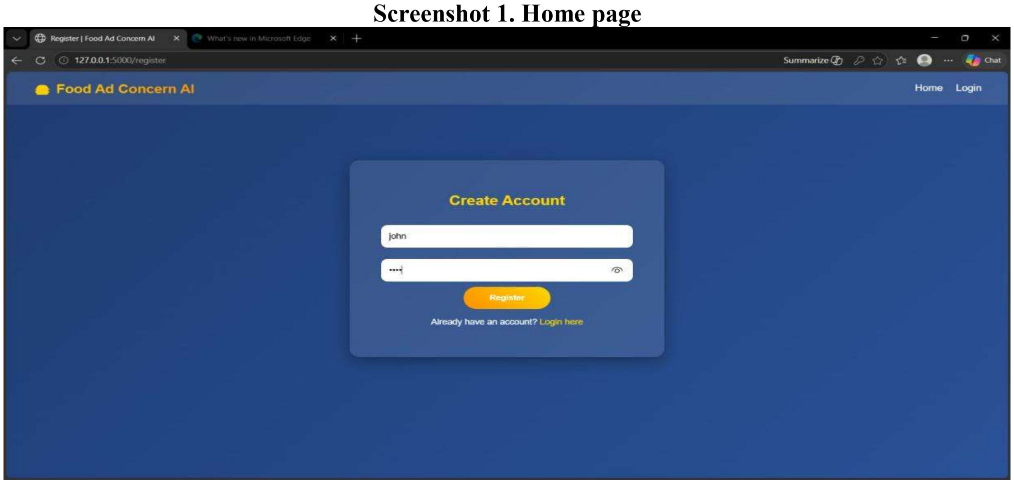


Fig 2. System Architecture

RESULT



Screenshot 1. Home page



Screenshot 2. Login page

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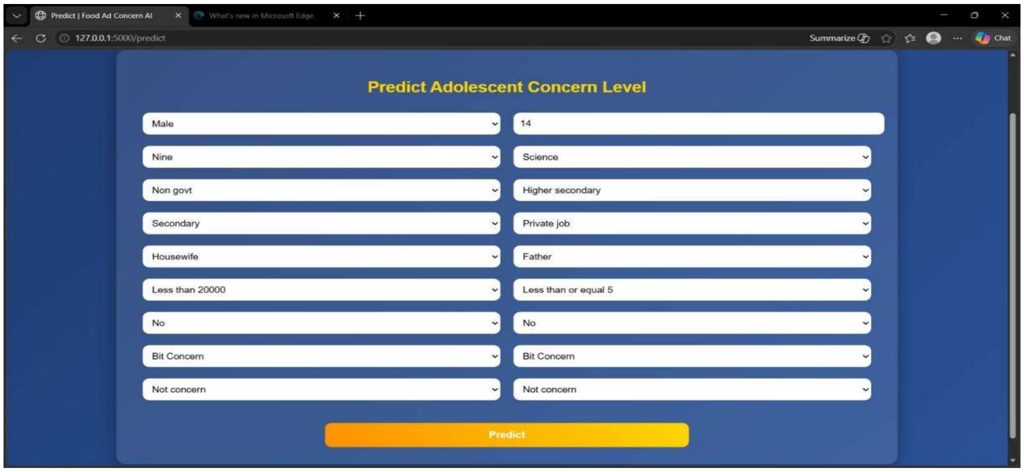
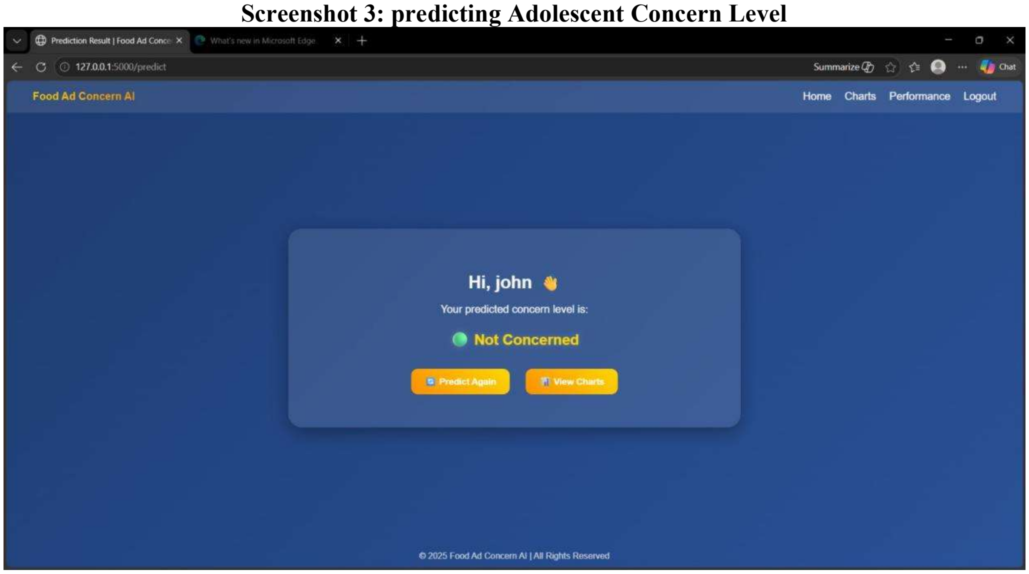


Screenshot 3: predicting Adolescent Concern Level



Screenshot 4. Final Result

CONCLUSION

This project successfully demonstrates the use of advanced machine learning techniques to predict adolescent concern toward unhealthy food advertisements. By analyzing demographic and behavioral factors, the XGBoost-based model provides reliable predictions that can assist in understanding how various advertisement types influence young audiences. The use of data preprocessing, feature embedding, and model optimization ensures better accuracy and robustness. The system highlights how artificial intelligence can support health education by identifying at-risk groups and helping policymakers design more responsible marketing strategies that reduce the negative impact of unhealthy food promotions.

In conclusion, the developed model offers an effective and scalable solution for addressing adolescent health concerns influenced by digital marketing. The predictive outcomes can guide stakeholders in creating awareness campaigns and regulatory frameworks that encourage healthier food choices. With further integration of larger datasets and real-time feedback systems, the model can evolve into a decision-support tool for governments, educational institutions, and health organizations. This research lays the foundation for using AI-driven insights to protect adolescents from misleading advertisements and promote long-term healthy lifestyle choices.

FUTURE SCOPE:

In the future, this system can be expanded to include real-time data collection from various digital platforms such as social media, video streaming, and online advertisements. By integrating continuous data streams, the model can adapt to changing advertisement trends and adolescent behavior patterns. Advanced deep learning models such as CNNs or transformer based architectures can be implemented to capture complex relationships among demographic, behavioral, and contextual

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features. This enhancement would lead to a more accurate and adaptive prediction system capable of handling large-scale, multi-dimensional data efficiently.

Furthermore, the system can be improved by incorporating sentiment and emotion analysis using natural language processing (NLP) techniques to analyze adolescents' reactions to advertisements. The addition of explainable visualization dashboards would help policymakers and researchers interpret predictions easily. Future versions can also support multi-language datasets to ensure the system's global applicability. A mobile-friendly and cloud-based deployment would allow broader accessibility, helping organizations monitor and promote health awareness initiatives more effectively across diverse populations.

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