IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 3 (2026)

ijerst.editor@gmail.com
editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

MACHINE LEARNING FRAMEWORK FOR ASSESSING ADOLESCENT CONCER TOWARD UNHEATHY FOOD ADVERTISEMENT

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ABSTRACT
For the purpose of raising health awareness and directing public policy, it is essential to forecast teenage concern over marketing for harmful foods. XGBoost, a gradient boosting machine learning model, is used in this work to forecast teenagers' degrees of concern based on behavioural and demographic characteristics. Age, parental education, and types of commercial exposure, such as free toys and celebrity endorsements, were among the survey data gathered from 1030 teenagers. To deal with unbalanced classes, the model is trained via synthetic oversampling and hyperparameter adjustment. By interpreting feature importance using explainable AI approaches (LIME and SHAP), it is possible to determine which elements have the greatest impact on teenage concern. The findings show that XGBoost achieves great prediction accuracy, providing a practical and understandable way to comprehend and lessen the effects of marketing for unhealthy foods.

1. INTRODUCTION

Consumer behaviour is influenced by advertising and paid promotions, particularly in the food and beverage industry, where these campaigns have an impact on eating habits. For example, a study found that youngsters in the US view more than 10,000 commercials for food-related products each year. The majority of these advertisements promote eating foods that are low in nutrition and high in calories [1]. Simultaneously, 80% of food marketing targeted to children focus more on taste, enjoyment, or convenience than fruits [2]. The accompanying commercials take advantage of Perceived and incorrect reasons that link food goods to various positive feelings include the celebrity effect, advertising incentives, and cartoon characters. Customers' perceptions of the products are clouded by such manipulations.

The marketing of harmful food products contributes significantly to the global burden of diet-related diseases. Advertising is the main driver of the more than 50% rise in adolescent obesity rates over the past 20 years [3]. Advertising has an impact on teenagers, who are especially vulnerable because of their developmental stage and the social and psychological clues included in the commercial products. Recognising how ads affect health awareness and concern levels is critical to designing interventions to make dietary changes and adjustments that will ultimately limit the lifetime risk of following unhealthy diets.

The widespread expansion of digital media and online marketing platforms has significantly increased adolescents' exposure to food advertisements. Many of these advertisements promote products that are high in sugar, salt, and unhealthy fats while offering limited nutritional benefits. Adolescents are particularly susceptible to persuasive advertising strategies due to their developing cognitive abilities and increasing independence in food choices. Marketing techniques such as celebrity endorsements, promotional gifts, attractive packaging, and emotional appeals are commonly used to influence purchasing behavior and dietary preferences. As a result, unhealthy food advertisements have become a growing public health concern, contributing to poor eating habits and increasing risks of obesity, diabetes, and other diet-related diseases among young populations.

Understanding how adolescents perceive and respond to unhealthy food advertisements is essential for designing effective health awareness programs and regulatory policies. While previous studies have extensively examined the relationship between food marketing and consumption behavior, limited attention has been given to predicting adolescents' levels of concern regarding such advertisements. Most existing research focuses on the direct health consequences of unhealthy dietary patterns rather than investigating the demographic and behavioral factors that shape awareness and concern. Consequently, there remains a significant gap in understanding how different advertising strategies influence adolescent perceptions and health consciousness.

Recent advances in machine learning have provided powerful tools for analyzing large-scale behavioral and demographic datasets. These techniques can identify complex relationships among variables and generate accurate predictions that support evidence-based decision-making. However, many machine learning models function as black-box systems, making it difficult to interpret how individual factors contribute to their predictions. This lack of transparency can limit the practical application of artificial intelligence in public health domains, where stakeholders require clear explanations to support policy formulation and intervention planning.

To overcome these limitations, Explainable Artificial Intelligence (XAI) methods have emerged as effective approaches for improving model transparency and interpretability. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) enable researchers to understand the contribution of individual features to model predictions. These methods provide valuable insights into the influence of demographic characteristics, parental factors, and advertisement-related attributes on adolescent concern levels. By combining predictive analytics with explainability, machine learning systems can become more trustworthy, interpretable, and useful for real-world applications.

In this study, an intelligent predictive framework is developed to analyze and classify adolescent concern levels toward unhealthy food advertisements. The proposed approach utilizes demographic, behavioral, and advertisement exposure characteristics to identify key factors influencing concern and awareness. Furthermore, explainable AI techniques are incorporated to provide transparent interpretations of prediction outcomes. The findings of this research can assist policymakers, educators, and public health organizations in developing targeted interventions, strengthening advertising regulations, and promoting healthier dietary behaviors among adolescents. By integrating advanced machine learning with explainable AI, this work contributes toward a more comprehensive understanding of the impact of unhealthy food advertising on adolescent health awareness and decision-making.

2. EXISTING SYSTEM OF PROJECT

The current system makes use of a Stacking Ensemble technique that combines Logistic Regression as the meta-learner with Random Forest, K-Nearest Neighbours, and Support Vector Machines as base learners. It focuses on using survey data to forecast teenage worry levels about marketing for unhealthy foods. To increase class balance and prediction accuracy, synthetic oversampling approaches and hyperparameter modification are used. This system shows the promise of ensemble learning techniques in managing multi-class classification issues in behavioural studies connected to health by offering a solid baseline with great predictive performance.

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. Feature importance can be inferred indirectly but lacks explicit interpretability. As a result, stakeholders such as policymakers and educators may find it challenging to extract actionable insights from the predictions, limiting its practical application beyond accurate classification.

The current system's reliance on precisely calibrated base learners and meta-learner setup is another drawback. Performance can be greatly impacted by any deviation in data preprocessing or class imbalance. Furthermore, the computational overhead of several models working simultaneously may limit real-time prediction scenarios. In spite of these difficulties, the approach provides a useful basis for predictive modelling in research on teenage behaviour. It offers trustworthy standards by which more recent models incorporating explainable AI or other algorithms can be evaluated.

ALGORITHM:

Stacking Ensemble with Random Forest, KNN, and SVM base learners.

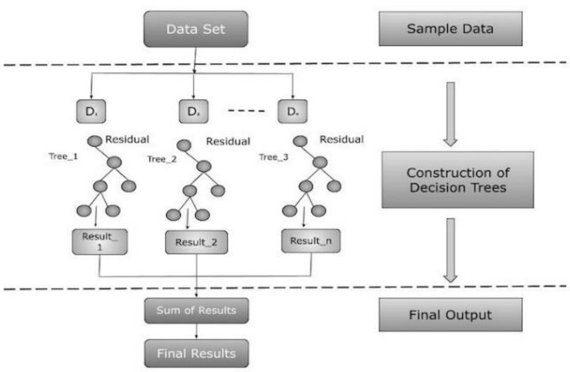
The existing system employs a Stacking Ensemble algorithm to predict adolescent concern levels regarding unhealthy food advertisements. It combines multiple base learners including Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) to capture diverse patterns in demographic and behavioral survey data. Logistic Regression acts as a meta-learner, aggregating predictions from the base models to produce final classification outputs for low, medium, and high concern levels. This ensemble approach improves predictive accuracy over individual models by leveraging complementary strengths.

The algorithm is trained using hyperparameter tuning and synthetic oversampling techniques to handle class imbalance in the dataset. While it achieves high predictive performance (~98.5% accuracy), the system primarily focuses on classification and does not explicitly explain feature contributions. The predictions provide reliable concern level categorization but require additional interpretability analysis to understand which factors, such as age, parental education, or advertisement type, most influence adolescent responses.

DRAWBACKS: -

- Limited Explainability
- Scalability Issues
- Computational Complexity
- Moderate Robustness

SYSTEM ARCHITECTURE:



3. PROPOSED SYSTEM

The gradient boosting machine learning algorithm XGBoost is used by the suggested method to forecast teenage worry levels about commercials for harmful foods. In contrast to the current Stacking Ensemble, XGBoost offers effective gradient-based optimisation that lowers computing overhead without sacrificing excellent prediction accuracy. The model makes use of survey characteristics like age, parental education, and types of exposure to advertisements, such as free gifts and celebrity endorsements. To address class imbalance, hyperparameter adjustment and artificial oversampling are used, guaranteeing accurate predictions in 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 suggested approach doesn't require a lot of retraining and is very scalable and adaptive to new data. The gradient boosting technique used by XGBoost guarantees resilience to noise and survey response fluctuation. Furthermore, compared to multi-model Stacking Ensembles, computational efficiency enables speedier forecasts. All things considered, the combination of Explainable AI and XGBoost offers a useful, comprehensible, and effective way to forecast teenage anxiety over advertisements for unhealthy foods, bridging the gap between precise predictive analytics and useful knowledge for educational and policy interventions.

ALGORITHM (XGBoost):

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

ADVANTAGES: -

- High Predictive Accuracy
- Scalability
- Robustness
- Actionable Insights

4. DATASET PREPARATION:

The dataset was constructed using a comprehensive question naire with multiple sections to collect demographic, behav ioral, and perceptual variables information. The questions then aimed to measure how much the participant was exposed to unhealthy food advertisements as the perceived effect TABLE 2. Survey sections and question types of the collected dataset. of such exposure in addition to overall health awareness. The questionnaire, demonstrated in Table 2, contained three significant parts, i.e., demographic characteristics, advertisement concerns and health awareness indicators. The demographic data were age, sex, parent education, and socioeconomic status of respondents. Concern regarding advertisement was assessed through a unipolar question (1-5), which referred to one's concern with a specific tactic, such as endorsement using celebrities, misleading claims, free toys, and others. Health awareness indicators were measured using binary (Yes/No) questions evaluating the ability of the participant to read nutritional labels accurately and ask questions about whether he/she wants transparency in food advertisements. The questionnaire was designed to comprehensively represent all relevant factors associated with the study while being transparent and straightforward for the respondents. The survey questions designed to assess the factors leading to concerns surrounding unhealthy food advertisements will be consistent with the aims of the inquiry concerning predicting and health awareness. Demographics, e.g., age, gender, class, and type of school, are significant in presenting patterns and dissimilarities concerning perception in different groups. Family background, parents' education, occupations, income, and household size help illuminate socioeconomic and generational influences on health awareness and perceptions with ads to some extent. Lifestyles such as smoking habits and chronic diseases give insights into health vulnerabilities and how they shape awareness. These questions center around advertisements, querying issues such as how accurate a message might be regarding nutrition or the persuasive effects of marketing tools, including celebrity endorsements and free toys- also critical to understanding how adverts shape consumer behavior. It also provides a behavioral aspect by detailed questioning of ring exposure, expenditure behavior, and long-term future health concerns, centering on the potential interface through which advertisement effects lead to health-conscious choices. In order to support targeted action and policy recommendations, this comprehensive approach, for instance, enables detailed questioning, meaning modelling of worry levels, finding behaviour patterns, and evaluating the proposed system's ability to forecast media impact. Several important demographic traits of the study participants from the used dataset are shown in Table 3. It shows that 1030 people between the ages of 13 and 18 participated in the study, with a balanced gender distribution. Table 4 displays the encoding strategy that was used to translate Likert-scale responses into categorical concern levels. The machine learning models use these labels—Not Concerned, Somewhat Concerned, and Very Concerned—as target variables.

5. TECHNIQUES USED IN PROJECT

The proposed system employs a comprehensive machine learning and explainable artificial intelligence framework to predict adolescent concern levels toward unhealthy food advertisements. Initially, survey data are collected from adolescents, capturing demographic information, parental background, advertisement exposure patterns, and health awareness indicators. The collected dataset undergoes several preprocessing steps, including missing value imputation, duplicate record removal, feature encoding, and normalization to improve data quality and model performance. To address the issue of class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) is applied, ensuring that all concern-level categories are adequately represented during model training.

For predictive modeling, the system utilizes the XGBoost algorithm, a powerful gradient boosting technique known for its high accuracy, scalability, and ability to handle structured datasets efficiently. Hyperparameter optimization is performed using GridSearchCV to identify the best model configuration and maximize predictive performance. The trained model classifies adolescents into different concern levels based on their responses and behavioral characteristics. To enhance transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques, namely Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), are integrated into the framework. LIME provides local explanations for individual predictions, while SHAP offers a global understanding of feature importance across the entire dataset. These techniques help identify the most influential factors, such as age, parental education, and advertisement characteristics, contributing to adolescent concern levels. By combining data preprocessing, SMOTE-based balancing, XGBoost classification, hyperparameter tuning, and explainable AI methods, the proposed system delivers an accurate, interpretable, and scalable solution for understanding the impact of unhealthy food advertisements on adolescent health awareness.

6. MODEL TRAINING

The performance of various machine learning models using their default hyperparameters is illustrated in Table 11. Most models, including Decision Tree, Random Forest, KNN, SVM, XGBoost, and Stacking Ensemble, achieved high accuracy, precision, recall, and F1 scores, generally above 98%. In contrast, the AdaBoost model demonstrated notably 141864 TABLE 10. Behavioral insights of the collected dataset. TABLE 11. Baseline model performance with default hyperparameters. TABLE 12. Model performance with optimized hyperparameters. lower performance with an accuracy of 76.49% and an F1 score of 0.76. Table 12 shows the performance of various machine learning models using optimized hyperparameters using the GridSearchCV technique. Most models, including Random Forest, KNN, SVM, XGBoost, and Stacking Ensemble, achieved very high and nearly identical performance, with an accuracy of approximately 98.50% and F1 scores of 0.98. In contrast, AdaBoost significantly underperformed, with an accuracy of 79.69% and an F1 score of 0.80. The confusion matrix in Fig. 4 illustrates the performance of the Stacking Ensemble model in classifying three levels of Concern: 0 (Not Concern), 1 (Bit Concern), and 2 (Very Concern). The model achieved high accuracy, correctly classifying 31 out of 33 instances for ‘‘Not Concern,’’ 76 out The private dataset used in this research gives a demographic behavioral count of 1030 respondents to ascertain the extent to which most respondents have been exposed to unhealthy food advertisements and related health concerns. The ages of the participants ranged between 13 and 18 years, with a mean age of 15.43 years and a standard deviation of 0.92 years. In the dataset, the gender distribution is also balanced. The participants’ educational background and socioeconomic status were also considered to study their effects on advertisement perception and health awareness, illustrated in Table 9. Table 10 illustrates behavioral insights derived from the curated dataset, with the percentage of participants exhibiting specific behaviors. 68% of people showed anxiety regarding unhealthy food advertisements, especially those associated with free toys and celebrity endorsement. Meanwhile, there was 71% of emphasis that food packages should indicate nutritional information

The model training process begins after completing data preprocessing and class balancing operations. The cleaned dataset is divided into training and testing subsets using a stratified train-test split approach, where 80% of the data is allocated for training and 20% for testing. Stratification ensures that the distribution of concern-level classes remains consistent across both datasets. To address class imbalance and improve the model's ability to learn minority class patterns, the Synthetic Minority Oversampling Technique (SMOTE) is applied to the training data before model development.

The proposed system utilizes the XGBoost (Extreme Gradient Boosting) algorithm as the primary classification model. XGBoost is selected due to its high predictive accuracy, robustness, and computational efficiency in handling structured survey data. The algorithm builds an ensemble of decision trees sequentially, where each new tree attempts to minimize the errors generated by previous trees. This boosting mechanism enables the model to capture complex relationships among demographic, behavioral, and advertisement-related features while reducing overfitting.

To obtain the optimal model configuration, hyperparameter tuning is performed using GridSearchCV. Several parameters, including the number of estimators, learning rate, maximum tree depth, subsampling ratio, and regularization parameters, are systematically evaluated to identify the best-performing combination. Cross-validation is employed during the tuning process to ensure model generalization and reliability. The optimized XGBoost model is then trained on the balanced training dataset and evaluated using the testing dataset.

The performance of the trained model is assessed using standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive evaluation of the model's ability to correctly classify adolescents into low, medium, and high concern categories. After achieving satisfactory predictive performance, Explainable Artificial Intelligence (XAI) techniques, including LIME and SHAP, are applied to interpret model predictions and identify the most influential features contributing to adolescent concern toward unhealthy food advertisements. This training framework ensures that the proposed system achieves both high predictive accuracy and meaningful interpretability.

7.RESULTS:

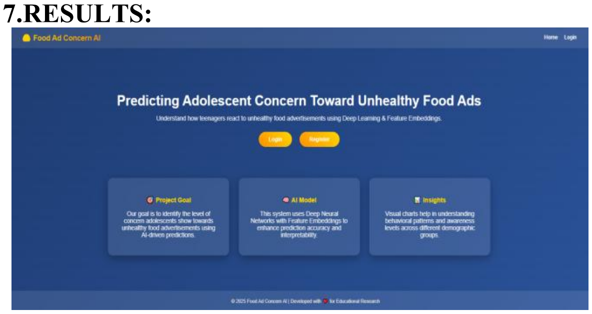


Fig:8.1 main website

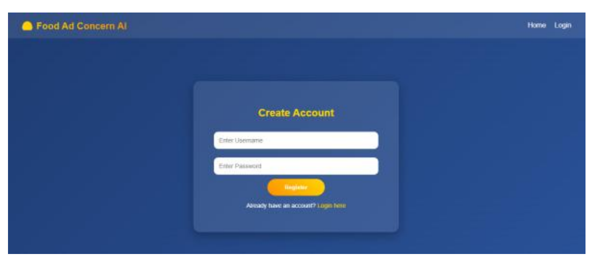


Fig:8.2 registration

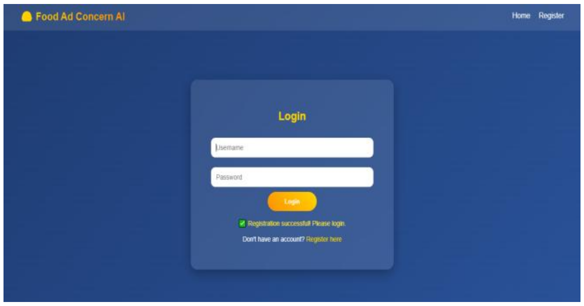


Fig: 8.3 login page

Fig:8.4 Uploaded Data

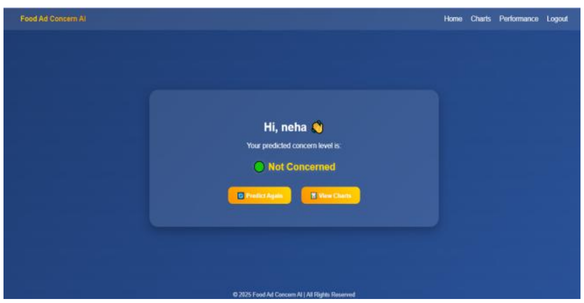


Fig: 8.5 Predicting Concern

Fig: 8.6 Visualization

The private dataset used in this research gives a demographic behavioral count of 1030 respondents to ascertain the extent to which most respondents have been exposed to unhealthy food advertisements and related health concerns. The ages of the participants ranged between 13 and 18 years, with a mean age of 15.43 years and a standard deviation of 0.92 years. In the dataset, the gender distribution is also balanced. The participants' educational background and socioeconomic status were also considered to study their effects on advertisement perception and health awareness, illustrated in Table 9. Table 10 illustrates behavioral insights derived from the curated dataset, with the percentage of participants exhibiting specific behaviors. 68% of people showed anxiety regarding unhealthy food advertisements, especially those associated with free toys and celebrity endorsement. Meanwhile, there was 71% of emphasis that food packages should indicate nutritional information.

The experimental evaluation demonstrates that the proposed XGBoost-based prediction model effectively classifies adolescent concern levels regarding unhealthy food advertisements. After applying data preprocessing, feature encoding, and SMOTE-based class balancing, the model achieved high classification performance across low, medium, and high concern categories. The optimized XGBoost classifier showed strong predictive capability, indicating its suitability for analyzing demographic and behavioral factors associated with adolescent perceptions of unhealthy food marketing.

Feature importance analysis identified age, parental education, and advertisement-related attributes as the most influential predictors. Advertisement strategies involving celebrity endorsements and free promotional items were found to have a significant impact on adolescent concern levels. These factors contributed substantially to the model's decision-making process and highlighted the role of marketing techniques in shaping health awareness among adolescents.

The integration of Explainable Artificial Intelligence techniques further validated the model's predictions. LIME explanations revealed the key features influencing individual classifications, while SHAP analysis provided a global interpretation of feature contributions across the dataset. Both methods consistently identified age, advertisement type, and parental education as dominant factors affecting concern levels. The agreement between local and global explanations enhanced the reliability and transparency of the proposed system.

Overall, the results confirm that the combination of XGBoost, SMOTE, hyperparameter optimization, LIME, and SHAP provides an accurate and interpretable framework for predicting adolescent concern toward unhealthy food advertisements. The proposed model offers valuable insights that can support public health initiatives, educational programs, and advertising policy development aimed at promoting healthier dietary behaviors among adolescents.

8. DISCUSSION AND CONCLUSION

The results of this study demonstrate that machine learning techniques can effectively predict adolescent concern levels toward unhealthy food advertisements using demographic, behavioral, and advertisement-related factors. The proposed XGBoost-based framework successfully identified key predictors influencing adolescent perceptions, including age, parental education, and advertisement characteristics such as celebrity endorsements and promotional incentives. These findings suggest that marketing strategies designed to attract young consumers significantly affect health awareness and concern levels, emphasizing the need for greater attention to advertising practices targeting adolescents.

The integration of Explainable Artificial Intelligence techniques further strengthened the effectiveness of the proposed system. LIME provided detailed explanations for individual predictions, while SHAP offered a comprehensive understanding of global feature importance across the dataset. Both methods consistently identified the same influential factors, increasing the transparency, reliability, and trustworthiness of the model. The ability to interpret prediction outcomes enables stakeholders to better understand how different demographic and behavioral characteristics contribute to adolescent concern regarding unhealthy food advertisements.

The study also highlights the importance of demographic and socioeconomic influences on health awareness. Adolescents with higher parental educational backgrounds generally exhibited greater concern toward unhealthy food marketing practices, indicating that family-level awareness and education play a critical role in shaping health-conscious behaviors. These insights can assist policymakers, educators, and public health organizations in designing targeted awareness programs and interventions aimed at improving nutritional literacy and promoting healthier lifestyle choices among adolescents.

Overall, the proposed framework provides an accurate, scalable, and interpretable solution for predicting adolescent concern toward unhealthy food advertisements. By combining XGBoost with LIME and SHAP, the system successfully bridges the gap between predictive performance and model interpretability. The findings contribute valuable knowledge for public health policy development, educational campaigns, and advertising regulation initiatives. Future research can extend this work by incorporating larger and more diverse datasets, exploring additional behavioral and psychological factors, and applying advanced explainable AI techniques to further enhance prediction accuracy and understanding of adolescent responses to unhealthy food advertising.

9. FUTURE ENHANCEMENT

Although the proposed framework achieved promising results in predicting adolescent concern levels toward unhealthy food advertisements, several opportunities exist for further improvement. Future research can incorporate larger and more diverse datasets collected from different geographic regions, cultural backgrounds, and age groups to improve the generalizability and robustness of the model. Expanding the study beyond adolescents to include children and adults would provide a broader understanding of how unhealthy food advertising influences different population segments.

Additional behavioral, psychological, and social factors such as peer influence, social media engagement, dietary habits, and emotional responses to advertisements can be integrated into the prediction framework to enhance model accuracy. Future studies may also employ longitudinal data to investigate the long-term impact of advertising exposure on health awareness, food choices, and lifestyle behaviors.

From a technical perspective, advanced machine learning and deep learning models can be explored and compared with XGBoost to further improve predictive performance. The integration of modern Explainable Artificial Intelligence techniques, including DeepLIFT, Shapley Regression Values (SRV), and attention-based interpretability methods, may provide deeper insights into feature interactions and model decision-making processes. Furthermore, the proposed framework can be extended into a real-time monitoring and decision-support system capable of analyzing advertising content and assessing its potential influence on adolescent health awareness. Such enhancements would strengthen the practical applicability of the system in public health monitoring, educational planning, and advertising regulation.

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