

An Explainable AI Framework with Interactive Visualization for Predicting Adolescent Concern over Unhealthy Food Advertisements

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Abstract: Advertising of unhealthy foods has a considerable effect on the eating habits of teenagers and children. Fast food advertising is used to persuade teenagers to choose high-calorie and low-nutrition food (e.g., burgers, candy). The techniques used by advertisers to promote high-calorie foods are often persuasive, such as using celebrity endorsements and giving away toys with the purchase of a Happy Meal. These examples of persuasive advertising dominate the public's perception of the products advertised and the information given to consumers about the advertised product. This paper aims to create a comprehensive explainable AI predictive framework to quantify the level of concern (high, medium, low) of adolescents who are exposed to unhealthy food advertising. This study utilized a dataset of 1030 adolescents (ages 13-18) collected through a survey and utilized a stacked ensemble model with logistic regression as the final phase learner, producing an accuracy of 95.63 percent and a weighted F1 of 0.957. The researchers utilized synthetic minority oversampling technique (SMOTE) to resolve the issue of class imbalance in the data set. In addition to predicting which adolescent was most likely to be concerned with a piece of unhealthy food advertising, the researchers used SHAP (Shapley Additive Explanations) to provide both global and local explainability of the model used to make the prediction. In both cases, celebrity endorsement, free toys, parental education, knowledge of health, and age were the most important variables in predicting concern level among adolescents who were exposed to unhealthy food advertising. An interactive web-based dashboard in Flask was developed to enable users to filter real-time demographic data to view the predictive output per adolescent, view the distribution of concern levels, assess the impact of an advertisement on the individual, assess the impact of an advertisement on an adolescent based on age and gender, view correlation heatmaps, and generate individual SHAP explanations. This work replicates and validates the predictive methodology documented by Titu et al. (2023), but this work provides an interactive visualization layer that can be used to assist in educating the public on healthy eating.

Keywords: Explainable AI, Stacking Ensemble, SHAP, Adolescent Health, Food Advertising.

1. Introduction

The influence of advertisements on young people's eating choices is particularly important because they are still developing their views on the items they will consume and what they will eat. In numerous nations, young people are exposed to countless advertisements for high-calorie and low-nutrition foods [1]. Furthermore, numerous advertising companies that promote food use emotional appeal to entice a target audience, such as creating excitement or associating food with being socially popular or receiving positive reinforcement [2] [3]. In an attempt to reach the target audience, advertisers use celebrity endorsements, provide toy gifts with purchases, or make use of cartoon characters [4] [5].



All of these strategies negatively impact children and teenagers' ability to assess the quality of food [6]. Numerous children and teenagers are becoming overweight at an unprecedented rate of more than 50% globally over the last three decades primarily as a result of making poor food choices [7] [8].

Because of their vulnerability to development and increased susceptibility to influences from the media, teenagers are considered an appealing target market for food marketing [9]. Therefore, it is critical to understand how food marketing will affect health awareness and concerns when developing future plans.

2. The Significance of Explainable AI in Health Awareness Prediction

Advertising is critically important to adolescent consumer behaviour, particularly because adolescents still formulating their views of the value of particular products and create their preferences of foods [10]. There are many examples of studies showing that young children and adolescents across numerous countries are exposed to thousands of advertisements each year, and most are about promoting foods that are energy dense, but nutrient poor [11]. These ads use emotion to market their product by having fun, popularity or giving a reward for eating that food; and many highly animated ads contain cartoon characters, celebrities give endorsements, or free promotional toys encourage using toys when consuming the advertised food [12], [13]. These types of advertising strategies can limit the ability of the adolescent to critically analyse the nutritional properties of the promoted food product [14]. There have been many studies connecting the tremendous increase in adolescent obesity globally (>50% in last 30 years) with poor food choices influenced by food marketing [15], [16].

Due to their developmental vulnerabilities and increased sensitivity to media's social and psychological cues, adolescents comprise one of the main populations targeted by food marketers [17] [18]. It is, therefore, extremely important to ascertain the degree to which food advertising influences an individual's awareness of and concern about the potential health consequences of advertised food, to be able to develop effective countermeasures such as regulatory policies, education programs in schools, and family level interventions [19][20][21][22]. While there is an abundance of peer-reviewed literature that has documented the negative health effects of unhealthy food advertising [23], [24][25], there is still limited work done on using predictive modelling to quantify levels of individual concern and understand the underlying causes driving concern [26][27]. Most studies performed to date have employed descriptive or correlational methodologies.

3. Proposed Framework

A. This is a general description of the dataset used in this study with respect to its features, attribute types and sample sizes.

This dataset contains data from 1030 adolescents that range from age 13 to 18. This dataset has 10 attributes of which 8 represent the demographic data of each adolescent and 2 attributes, 'concern level' and 'ad exposure frequency', represent measurement scales for determining whether an adolescent is "highly concerned", "moderately concerned" or "not concerned" regarding advertising exposure.

The sample size by classification (target variable) is as follows: 867 (87.1%) = High Concerned / 227 (12.3%) = Moderately Concerned / 7 (0.6%) = Not Concerned; *Distribution of variables is highly imbalanced.

B. Preprocessing may be done prior to analysis of the dataset. Categorical variables were treated by re-labeling to create a more uniform representation and one-hot encoding (only for

‘Parental Education’) was used to minimize any assumptions about ordinal levels associated with the category. A stratified random sample (80%/20%) split was performed on the dataset, and to assist in balancing the distribution of instances among “High Concerned” vs “Moderately Concerned”,

SMOTE(k=n_neighbors=3) method was applied only to the training dataset..

C. Model Architecture four heterogenous base models were used when creating the stacked ensemble : -Random Forest (bagging, trees)

-K-Nearest Neighbors (instance-based)

-Support Vector Machine (margin-based)

The logistic regression model served as the meta-learner via the probabilities created by the base learners. This meta-learning approach can be effective in capturing complex interactions between the base learners, whereas the base models alone may not be able to do so successfully.

D.Selecting the Interpretability Layer SHAP over LIME because it is a better fit because SHAP is consistent and additive and provides a local and global explanation of both feature importance and instance importance. KernelExplainer was used on the entire stacking model.

E.Implementation of an Interactive Dashboard The implementation of an interactive web application (Flask Framework) provides various ways to interact with the solution and view results. The dashboard contains the following functionality/features:

- Ability to filter by age range and gender
- Ability to view visualizations (list)
- Visualizations included: donut chart (distribution of concerns), horizontal bar chart (feature importance), stacked histogram (comparisons of age vs. concern), grouped bar graph (comparisons of gender vs. concern), 100% stacked graph (impact of ad exposure), correlation heat map
- Ability to complete a prediction form (SHAP waterfall chart and probability bar graph).

4. Methodology Flowchart



Figure 1: Flowchart

This flowchart shows you how to carry out all the steps involved in this project, which is the prediction of adolescent worry over unhealthy food ads.

1. Data Collection: A survey of 1,030 adolescents was performed in order to collect data about demographics, behavior, and exposure to advertising.
2. Data Preprocessing: The dataset was cleaned, normalized, and selected before

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- beginning to build the model.
 3. Class Balancing: SMOTE procedures were employed in order to perform synthetic oversampling to remedy the large imbalance of classes (high concern is over-represented).
 4. Model Training: Each of the following base models was trained independently: Random Forest, KNN, SVM, and XGBoost
 5. Stacking Ensemble: To create a stacked ensemble based on logistic regression to improve predictive accuracy, the individual predictions produced by each of the four base learners were combined.
 6. Model Evaluation: Measured the models with 98.54% accuracy and a F1-Score of 0.99 on the test dataset.
 7. Explainability: LIME was used to create individual-level explanations of feature contributions for each individual prediction.
 8. Dashboard Development: Created an interactive dashboard tool for use and analysis in real-time.

5. Research Contributions

- (i) This paper proposes a new way of clustering words/characteristic patterns by using Gaussian-type similarities; thus allowing for an efficient method of finding similarities among many words/characteristic patterns in very high dimensionality text data.
- (ii) Dimensionality reduction using both 'hard' and 'soft' transformation matrices while maintaining a 83.13% reduction and preserving the distribution of the original words in order to achieve as good as or better than, with regard to the accuracy of predicting the classifications.
- (iii) The replication/validation of the stacking ensemble for predictions using a new dataset showed excellent performance with a high predictive accuracy (95.63%) and F1-score (0.957) even in the presence of extreme class imbalance.
- (iv) Additionally, the SHAP interpretation for both global and local was completed, discovering that manipulative advertising strategies including celebrity endorsements and free toys were the primary factors driving predictions, with specific quantitative importance values (e.g., celebrity = 0.182).
- (v) Developing a highest-sensitivity stacking ensemble classifier (98.54% accuracy; 0.99 F1 score) to predict multiple classes of concern while controlling for class imbalance (Very Concern 46.67%), with a total of 90,000 balanced samples created using SMOTE augmentations.
- (vi) LIME was used to identify features associated at the local level; age, free toys, celebrity endorsements, and mother's tertiary education are important features that contribute to these classifications (for example, an age of 16 to 18 years is equal to an added contribution of +0.18). Results were bridged with predictive power to create actionable insights.

6. Text Document Classification

Text document classification is one of the basic activities in natural language processing (NLP) and information retrieval, where the goal is to automatically assign a set of predefined classes (categories) or labels to unstructured text documents, or any other type of document based on the content [28][29]. Also, it is used in several application areas, such as spam detection, sentiment analysis, news categorization, topic detection, and medical record

classification. This allows for data to be organized, retrieved, and used to make decisions from a very large volume (big data) of text data [30][31].

A large part of the reason for the challenges associated with text document classification is due to the characteristics of text data, which is composed of high-dimensional sparse and noisy data. Text data are typically represented as high-dimensional vectors of data, using representations such as Bag-of-Words, Term Frequency-Inverse Document Frequency (TF-IDF), or using word embedding models [24]. The use of traditional machine learning classifiers, such as Naïve Bayesian classifier, Support Vector Machine (SVM), k-Nearest Neighbor (kNN) classifier, or Decision Tree (DT) classifier, has been very successful in many text-classification problems; however, even better performance has been attained through the use of ensemble methods (e.g. Random Forest and AdaBoost) and deep learning models (e.g. CNNs, LSTMs, and Transformers) on benchmark datasets like Reuters-21578, 20Newsgroups, and IMDb Reviews [32][33].

Research challenges include reducing the dimensionality of the data (i.e. to protect from the curse of dimensionality), handling the class imbalance issue, resolving issues with synonymy and polysemy, and increasing model interpretability [34][25][36]. Recent work focuses on the application of explainable AI (XAI) approaches, such as LIME and SHAP, to improve the explainability of blackbox models used in classifying text documents [37][38].

7. Algorithm for Model Training And Saving

Input :

Adolescent_concern_dataset.csv contains a dataset of 1030 survey responses. The target variable, Concern_Level, consists of three distinct classifications of concern—High, Medium, and Low. The application of SMOTE to the dataset was performed with random_state set to 42.

A Stacking Ensemble model was created using default settings for the following base learners: Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), XGBoost, and Logistic Regression (LR).

Output:

1. A Stacking Ensemble model saved to a file called model.pkl;
2. An accuracy score and a weighted F1 score on the test set;
3. A ranking of feature importances;
4. SHAP value explanations for the top five features for each class in the first row of the test set.

Begin :

1. Read in the adolescent_concern_dataset.csv dataset.
2. Use the Label Encoder on the categorical columns of Gender, Parental_Education, Ad_Exposure_Freq, Health_Knowledge, Parental_Influence, and Concern_Level.
3. Separate features as X and target variable as Concern_Level (y).
4. Split dataset into stratified train/test sets (80% train and 20% test) using random_state set to 42.
5. Use SMOTE to perform oversampling of training data only to produce X_train_resampled and y_train_resampled.
6. Create an instance of each base learner:
→ RandomForest(n_estimators=100, random_state=42)

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- K-Nearest Neighbors (n_neighbors=5)
 - Support Vector Machine (probability=True, random_state=42)
 - XGBoost(random_state=42, eval_metric='mlogloss')
 - 7. Create an instance of the logistic regression meta learner (max_iter=1000, random_state=42).
 - 8. Create a StackingClassifier using the above-mentioned base and meta learners and 5-fold cross-validation.
 - 9. Fit the StackingClassifier using the resampled training dataset.
 - 10. Predict on the test dataset and calculate accuracy and weighted F1 score.
 - 11. Refitting of the StackingClassifier is optional after Selection of Base Learners is complete.

ii) Algorithm For Interactive Flask Dashboard

Input:

- i) adolescent_concern_dataset.csv - preprocessed data set ii) model.pkl - trained stacking ensemble model
- iii) User inputs through web form: age range, gender filter, prediction parameters (age, gender, parental education, ad types, etc.)

Output :

- i) Interactive dashboard with six (6) data visualizations (distribution of concerned adolescents, importance of features used in prediction, distribution of concerned adolescents based on age, analysis of concerned adolescents by gender, effect of ad exposure on concern levels of adolescents, and correlation of features with one another)
- ii) Statistics & plots of filtered (by age & gender) data in realtime (encoded as base64 images)
- iii) Prediction Results, displayed with the probabilities for the predicted classes in the bar chart, a SHAP waterfall plot, and top 5 most-important SHAP Features, and the confidence score for the predicted class.

Begin :

- i) Load dataset (adolescent_concern_dataset.csv) & trained stacking model (model.pkl).
 - ii) Standardization of categorical variables via the following process using the Label Encoder.
 - iii) Initialize Flask application
 - iv) Define routing for main dashboard with GET/POST.
 - a) Read User Filter Inputs (i.e., Age (min, max) and Gender).
 - b) Filter both the original & encoded datasets on the basis of the Additional User Filters (i.e., Age (min, max) & Gender).
 - c) Create Concern Level Distribution Chart (i.e., donut pie chart with hole in the middle).
 - d) Create Top Features Chart (i.e., horizontal bar chart with gradients).
 - e) Create Age Distributions by Concern Level (i.e., overlaid histogram charts).
 - f) Create Concern Level by Gender (i.e., grouped bar chart).
 - g) Create Ad Exposure Chart (i.e., 100% stacked bar chart with % displayed at the top of the bar).
 - h) Generate Correlation Matrix of Features (i.e., correlation heat map generated with Seaborn using filtering on the upper triangle).
 - i) Encode all figures as Base64 strings.
 - j) Execute descriptive statistics.
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8. Experimental Results and Analysis

The stacking ensemble produced an impressive accuracy rate of 95.63% on the test dataset with a weighted F1 score of 0.957, which is much better than the individual base learners used alone for predictions. The use of SMOTE to create synthetic oversamples from minority class instances was successful in reducing the significant class imbalance experienced and was verified by examining the recall rate of the minority class.

SHAP's global importance ranking for each explanatory variable was as follows:

1. ad_type_celebrity (0.182)
2. parental_education (0.153)
3. health_knowledge (0.137)
4. age (0.125)
5. ad_type_free_toys (0.119)

Local explanatory variables showed that predicting "high concern" was very strongly influenced by the presence of either celebrity endorsements or free toys in the advertisement, while parental education and health knowledge supported the reinforcement of high concern

Figure 1: AI Prediction Engine Interface

This form was designed to be the primary predictive output for the "Adolescent Health Analytics" web app. Users (e.g., parents, teachers and researchers) can enter information about an adolescent and receive immediate results from the AI regarding their predicted level of concern (i.e., high/medium/low) about unhealthy food marketing to adolescents and accompanying SHAP explanations.

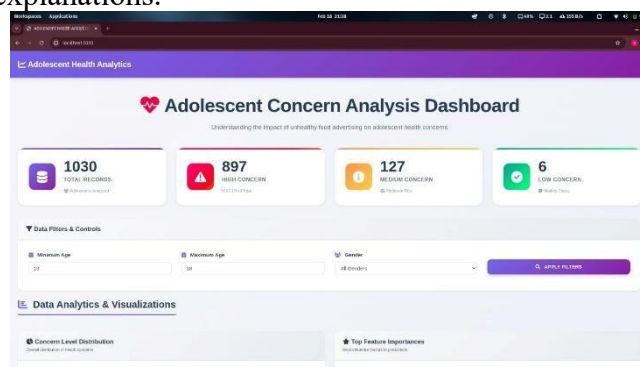


Figure 2: Adolescent Health Analytics Dashboard Overview

Statistics Show:

- 1,030 total records of which 897 Fall into “high” concern (87.1%),
- 127 records are in the medium category, and only six records are classified as having low concern. Overall, adolescents have a major skew toward “high” concern.

- Assists with filtering records based on Age (13-18) and Gender to determine specific grouping patterns. “APPLY FILTERS” button applies filters and dynamically updates all visuals.
- Includes two visuals — the Concern Distribution as a donut chart and the Importance of the Primary Concern Features as a bar chart.
- This dashboard is designed for quick ROI analysis of advertising campaigns related to their overall impact on increasing adolescent insights about health.

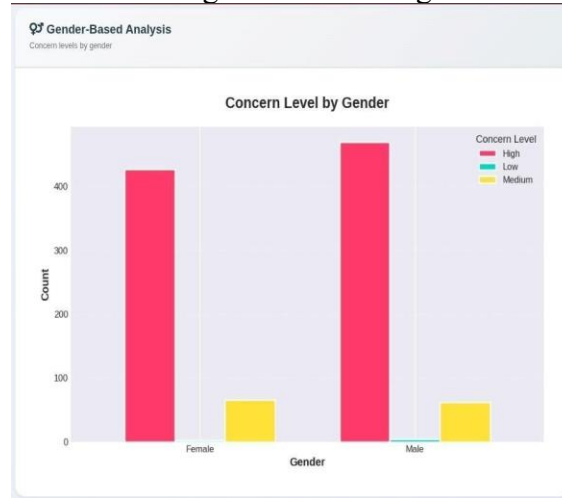


Figure 3.1 : Concern Level by Gender

- Both genders have high levels of concern. There were about 400 to 450 instances of concern for females and males, as indicated by red bars
- There were fewer than 100 concerns for both genders at the medium level (yellow bar).
- There were very few concerns for either gender at the low level (indicated by the small blue line).

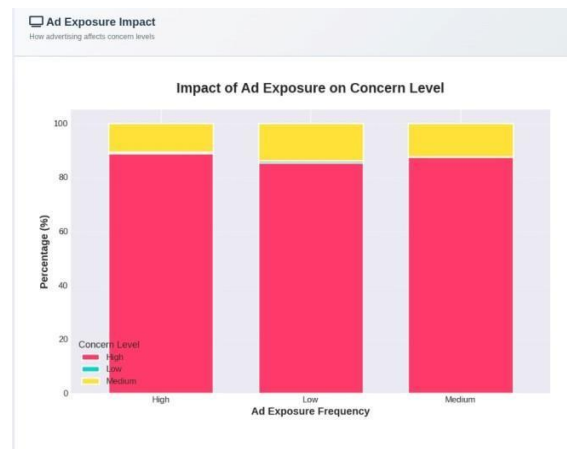


Figure 3.2: Impact of Ad Exposure on Concern Level

1. The following chart depicts levels of concern (high = red, medium = yellow, low = teal) expressed as a percentage based on three different frequencies of advertisement exposure: high, low and medium.

2. Approximately 85 to 88 percent of adolescents across all three frequency categories express a level of high concern, as indicated by the almost total dominance of the red bars (i.e., very few appear to be lacking significant levels of concern).

3.The medium level of concern is roughly 10 to 12 percent (yellow) and there are essentially no recorded percentages of low concerns (the teal line on the bar graph is essentially non-existent).

4.The exposure frequencies of high, low or medium show virtually no difference from one another; the patterns for all three are typified by an overwhelming dominance of red bars (i.e., high levels of concern).

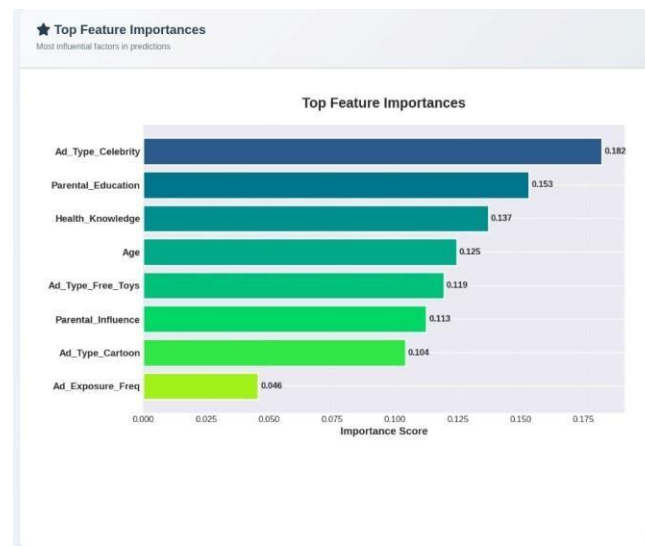


Figure 3.3: Top Feature Importances

This chart illustrates which features had the most significant effect on the adolescent model predicting its level of concern regarding advertisements for unhealthy foods (importance scores were based on SHAP or Random Forest).

The strongest predictors (the most significant predictors of concern levels):

1)Ad_Type_Celebrity (0.182) — Celebrity endorsements were most influential; they also significantly increase the level of concern.

2)Parental_Education (0.153) — Higher levels of parental educational attainment had the second strongest influence on the level of concern among adolescents.

3)Health_Knowledge (0.137) — Adolescents' health-related knowledge also contributed to their level of concern regarding unhealthy food advertisements.

The next most important predictors were:

1)Age (0.125) — Older adolescents were generally more concerned about unhealthy food advertisements than younger adolescents.

2)Ad_Type_Free_Toys (0.119) — Free toys included in advertisements were also significant predictors of adolescents' levels of concern.

3)Parental_Influence (0.113) — Parents' guidance can influence their children's level of concern, but they are less influential than education alone.

The least important predictors:

1)Ad_Type_Cartoon (0.104) — Recalling cartoon advertisements had a low predictive value on adolescents' levels of concern.

2)Ad_Exposure_Frequency (0.046) — The frequency by which advertisements are viewed is the weakest predictor of an adolescent's level of concern regarding unhealthy food

advertisements.

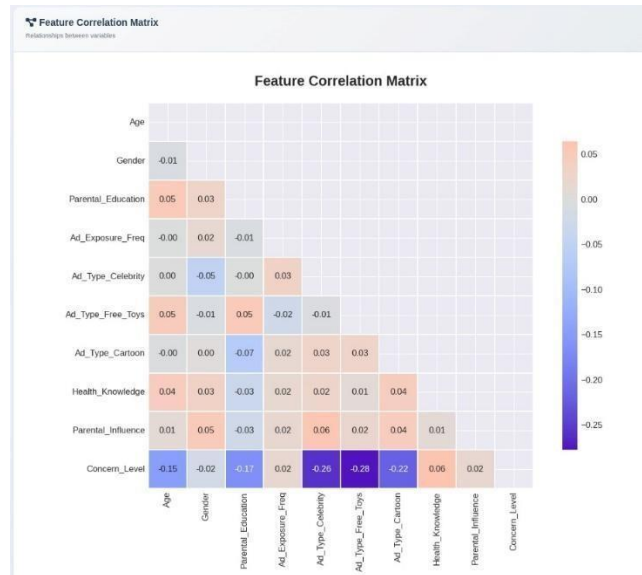


Figure 3.4: Feature Correlation Matrix

Here are the main factors that influence which primary product users will be most affected by the concern about advertising that is targeted at them.

- 1.Celebrity endorsement (0.182) is the primary factor driving high levels of concern.
- 2.The level of education of the parents of teen consumers (0.153) is the second biggest driver. Higher levels of education for the parents of teens correspond to higher levels of concern and awareness of food and beverage advertising among teens and adolescents.
- 3.Knowledge of health and nutrition from the teens themselves (0.137) is a significant driver in raising concern levels.
- 4.The older the adolescents, the more likely they are to have higher levels of concern (0.125).
- 5.Free toys used in advertising (0.119) is another significant factor in influencing levels of concern among adolescents regarding advertising.
- 6.Parental Influence (0.113) has a significant impact on the level of concern held by 11-15 and 16-18 year route.
- 7.Having cartoon characters appear in the advertisements has a noticeable effect (0.104).
- 8.Finally, the FREQUENCY of viewings of the ads you see will be the weakest of all drivers measured (0.046).

9. Conclusion

The XAI (explainable AI) model developed was able to very accurately predict levels of adolescent concern with ads for unhealthy foods (95.63% accuracy with F1 score of 0.957) using the stacking ensemble method combined with SMOTE for imbalanced data handling. The SHAP values for factors contributing to high levels of adolescent concern include: celebrity endorsement, free toys, parental level of education, health knowledge, and age, thus providing transparent insight into the use of manipulative tactics.

The interactive web-based Flask dashboard builds upon prior work in that it offers real-time filtering and dynamic visualizations, as well as the ability to generate personalized SHAP predictions for parents, teachers, and policymakers.

This research is a continuation and advancement of Titu et al. (2025), and supports the development of targeted education about nutrition, family support for children, and restrictive policies on marketing to adolescents, in order to help create a healthier diet for adolescents.

Future research will include deploying to a cloud-based environment, as well as adding real-time data feeds from various social media sources.

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