

EXPLORING DIETARY INFLUENCES ON OBESITY THROUGH PREDICTIVE MACHINE LEARNING TECHNIQUES

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ABSTRACT

Obesity is a prevalent global health issue, with multifaceted causes, including genetic, environmental, and lifestyle factors. One significant aspect contributing to obesity is eating habits, making it crucial to understand the relationship between dietary choices and obesity levels. This research explores the application of machine learning (ML) techniques to predict obesity levels based on eating habits. Here, a comprehensive dataset encompassing diverse demographic information, dietary patterns, and obesity levels of individuals is considered. Various machine learning algorithms, including Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, are employed to develop predictive models. Feature selection methods are employed to identify the most influential dietary factors affecting obesity. The proposed approach assesses the model's performance using metrics such as accuracy, precision, recall, and F1-score. Additionally, ML models demonstrate promising predictive capabilities, with certain algorithms outperforming others in accuracy and reliability. Moreover, feature importance analysis identifies specific food groups and consumption patterns strongly associated with obesity, providing valuable insights for targeted interventions and personalized dietary recommendations. This research contributes to the growing field of predictive healthcare analytics, offering a data-driven approach to address obesity-related challenges. The outcomes have implications for public health policies, nutrition education programs, and personalized healthcare initiatives, aiming to mitigate the obesity epidemic and promote healthier lifestyles.

Keywords: Obesity prediction, Machine learning, Dietary patterns, Feature selection, Predictive healthcare.

1. INTRODUCTION

Obesity has become a global health concern, with rising rates worldwide. It is associated with various health issues such as diabetes, cardiovascular diseases, and certain types of cancer. Understanding and predicting obesity levels based on eating habits is crucial for preventive healthcare and policy making. Early attempts to understand the link between eating habits and obesity date back to the mid-20th century. Initially, research focused on simple correlations. As technology advanced, data collection methods improved, leading to more nuanced studies. With the rise of computers and data science, ML approaches were introduced to analyze complex relationships between various factors, including eating habits and obesity levels based on eating habits, ML algorithms process various features like food types, portion sizes, meal timings, and physical activity levels to create predictive models. The need for predicting obesity levels based on eating habits is multifaceted. It aids public health officials in designing effective interventions and policies. Additionally, it helps individuals make informed decisions about their lifestyles, leading to healthier choices and reduced healthcare costs. Obesity poses a widespread global

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health concern, influenced by a complex interplay of genetic, environmental, and lifestyle factors. Among these, eating habits play a pivotal role, underscoring the need to unravel the intricate relationship between dietary choices and obesity levels. This study employs advanced machine learning (ML) techniques to predict obesity levels based on a comprehensive dataset encompassing diverse demographic information, dietary patterns, and individual obesity status. The research explores the efficacy of various ML algorithms, such as Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, in constructing predictive models. To enhance model accuracy, feature selection methods are applied to identify the most impactful dietary factors influencing obesity. The proposed methodology evaluates model performance using key metrics, including accuracy, precision, recall, and F1-score. Notably, the ML models exhibit promising predictive capabilities, with certain algorithms surpassing others in terms of accuracy and reliability.

2. LITERATURE SURVEY

S. Maria [1] proposed that approximately about two billion peoples are affected by obesity that has drawn significant attention on social media. As the sedentary lifestyle which includes consumption of junk foods, no physical activities, spending more on screen, etc are one of the causes of obesity. Obesity generally refers to that a person's body possessing an excessive amount of fat. There is a huge increase in obesity cases which resulting cardiac problems, stroke, insomnia, breathing problems, etc. Type-2 diabetes has been detected in the patients suffering from obesity recently. The studies showing that there are lot of young individuals and children's who has been suffering from overweight and obesity issues in Bangladesh. Here, a strategy for predicting the risk of obesity is proposed that makes use of various machine learning methods. The dataset Obesity and Lifestyle taken from Kaggle site which is collection of different data based on the eating habits and physical conditions, such as height, weight, calorie intake, physical activities are just a few of the 17 different categories in the dataset that reflect the elements that cause obesity. Several machine learning methods include Gradient Boosting Classifier, Adaptive Boosting (ADA boosting), K-nearest Neighbor (K-NN), Support Vector Machine (SVM), Random Forest, and Decision Tree. T. Cui [2] proposed in recent decades, there has been increasing concern about obesity in adolescents and adults. Obesity can cause many physical health problems and affect people's quality of life. So people are starting to look at the factors that lead to obesity and predict the emergence of obesity. This research presents an estimation of obesity levels based on eating habits, physical condition, and other factors, using a dataset found on UCI Machine Learning Repository. This dataset contains 17 attributes and 2111 records. The labels of this dataset are classified as Insufficient Weight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I, Obesity Type II and Obesity Type III. In this research, three major methods are chosen for prediction: Decision Trees, Logistic Regression, and K Nearest Neighbor. Finally, the result obtained by Decision Trees has the best accuracy.

N. P. Sable [3] encountered More than 2.1 billion people worldwide are shuddering from overweightness or obesity, which represents approximately 30% of the world's population. Obesity is a serious global health problem. By 2030, 41% of people will likely be overweight or obese, if the current trend continues. People who show indications of weight increase or obesity run the danger of contracting life-threatening conditions including type 2 diabetes, respiratory issues, heart disease, and stroke. Some intervention strategies, like regular exercise and a balanced diet, might be essential to preserving a healthy lifestyle. Thus, it is crucial to identify obesity as soon as feasible. We have collected data from sources like schools and colleges within our organization to create our dataset. A vast range of ages is considered and the BMI value is examined in order to determine the level of obesity.

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The dataset of people with normal BMI and those at risk has an inherent imbalance. The outcomes are collected and showcased via a website which also includes various preventive measures and calculators. The outcomes are promising, and clock an accuracy of about 90% Singh, B [4] observed individuals developing signs of weight gain or obesity are also at a risk of developing serious illnesses such as type 2 diabetes, respiratory problems, heart disease and stroke. Some intervention measures such as physical activity and healthy eating can be a fundamental component to maintain a healthy lifestyle. Therefore, it is absolutely essential to detect childhood obesity as early as possible. This paper utilises the vast amount of data available via UK's millennium cohort study in order to construct a machine learning driven model to predict young people at the risk of becoming overweight or obese. The childhood BMI values from the ages 3, 5, 7 and 11 are used to predict adolescents of age 14 at the risk of becoming overweight or obese. There is an inherent imbalance in the dataset of individuals with normal BMI and the ones at risk. The results obtained are encouraging and a prediction accuracy of over 90% for the target class has been achieved. Various issues relating to data preprocessing and prediction accuracy are addressed and discussed. Cheng [5]. used 11 classification algorithms (logistic regression, radial basis function (RBF), naïve Bayes, classification via regression (CVR), local k-nearest neighbors (k-NN), a decision table, random subspace, random tree, a multi-objective evolutionary fuzzy classifier, and a multilayer perceptron) to predict obesity in adults and achieved a highest overall accuracy of 70% with a random subspace algorithm [5]

Cervantes. [6]. developed decision tree (DT), k-means, and support vector machine (SVM)-based data mining techniques to identify obesity levels among young adults between 18 and 25 years of age so that interventions could be undertaken to maintain a healthier lifestyle in the future [6].

Gupta [7]. developed a deep learning model (long short-term memory (LSTM)), which predicted obesity between 3 and 20 years of age with 80% accuracy using unaugmented electronic health record (EHR) data from 1 to 3 years prior [7]. Marcos-Pasero [8] used random forest (RF) and gradient boosting to predict the BMI from 190 multidomain variables (data collected from 221 children aged 6 to 9 years) and determined the relative importance of the predictors [8] Zare [9]. used kindergarten-level BMI information, demographic, socioeconomic information such as family income, poverty level, race, ethnic compositing, housing, parent education, and family structure to predict obesity at the fourth grade and achieved an accuracy of about 87% by using logistic regression and an artificial neural network [9] Zare [10]. used kindergarten-level BMI information, demographic, poverty level, race, ethnic compositing, housing, parent education, and family structure to predict obesity at the fourth grade and achieved an accuracy of about 87% by using logistic regression and an artificial neural network [9] Zare [10]. used kindergarten-level BMI information, demographic, socioeconomic information such as family income, poverty level, race, ethnic compositing, housing, parent education, and family structure to predict obesity at the fourth grade and achieved an accuracy of about 87% by using logistic regression and an artificial neural network [10] Fu,et.al [11]. developed an ML-based framework to predict childhood obesity by using health examination, lifestyle and dietary habits, and anthropometric measurement-related data [11].Pang [12]. proposed ML models to predict childhood obesity from EHR data [12]

3. PROPOSED METHODOLOGY

Dataset Collection and Characteristics: A dataset incorporating a broad spectrum of information is collated, capturing demographic details, dietary preferences, and obesity levels of individuals. This diverse dataset forms the foundation for training and evaluating machine learning models.

Data Preprocessing: To ensure the reliability of the dataset, a meticulous data preprocessing phase is undertaken. This involves handling missing values, standardizing data formats, and addressing outliers. Cleaning the dataset lays the groundwork for accurate and meaningful model training.

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Data Splitting: The dataset is then partitioned into training and testing sets. The training set is utilized to teach the machine learning models, while the testing set evaluates the model's predictive performance on unseen data, simulating real-world scenarios.

Machine Learning Algorithms: Various machine learning algorithms, including Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, are employed. Each algorithm is trained on the dataset, learning patterns and relationships between dietary factors and obesity levels.

Feature Selection Methods: Feature selection methods are applied to identify the most influential dietary factors affecting obesity. This step is crucial for refining the model and focusing on the most relevant features, improving both accuracy and interpretability.

Performance Evaluation: The performance of the machine learning models is rigorously assessed using key metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in predicting obesity levels based on eating habits.

Prediction from Test Data: The trained models are then applied to the test dataset to predict obesity levels based on individuals' eating habits. This step is crucial for gauging the real-world applicability and reliability of the developed models.



Figure 1: Block diagram of proposed system.

3.2 Data Preprocessing

In preparing the data for our research on predicting obesity levels based on eating habits using machine learning, several crucial preprocessing steps were implemented to ensure the reliability and accuracy of our models. The dataset employed in this study is comprehensive, covering a wide range of demographic information, dietary patterns, and obesity levels of individuals. Firstly, data cleaning procedures were applied to handle missing values, outliers, and inconsistencies. Missing values were either imputed using appropriate methods or, if feasible, the corresponding records were excluded. Outliers, which could potentially skew the results, were identified and addressed to maintain the integrity of the dataset. Next, feature engineering played a pivotal role in shaping the dataset for effective model training. This involved creating new variables or modifying existing ones to capture relevant information. For instance, we derived additional features to represent cumulative dietary indicators, amalgamating multiple food groups to better reflect overall eating habits.

Furthermore, categorical variables were appropriately encoded to numerical formats, ensuring compatibility with machine learning algorithms. This step involved techniques like one-hot encoding or label encoding, depending on the nature of the categorical data. This transformation facilitates the

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seamless integration of categorical variables into the predictive models. In the context of feature selection, a meticulous process was undertaken to identify the most influential dietary factors contributing to obesity. Various techniques, such as recursive feature elimination and correlation analysis, were employed to pinpoint the key features. This step was crucial in enhancing the efficiency of our models by focusing on the most relevant input variables. To address potential biases and ensure fairness in our predictions, demographic variables were carefully examined for any disparities. Stratified sampling or balancing techniques were applied when necessary to account for imbalances in the distribution of certain demographic groups.



Figure 2: Diagram of extremely randomized tree classifier.

Extremely Randomized Trees, also known as Extra Trees, construct multiple trees like RF algorithms during training time over the entire dataset. During training, the ET will construct trees over every observation in the dataset but with different subsets of features. It is important to note that although bootstrapping is not implemented in ET's original structure, we can add it in some implementations. Furthermore, when constructing each decision tree, the ET algorithm splits nodes randomly.

4. RESULTS AND DISCUSSION

The dataset consists of several features related to individuals and their lifestyle factors. Here's a description of each column in the dataset:

- Gender: Represents the gender of the individual (e.g., Male or Female).
- Age: Represents the age of the individual.
- Height: Represents the height of the individual.
- Weight: Represents the weight of the individual.
- family_history_with_overweight: Indicates whether there is a family history of overweight.
- FAVC (Frequency of eating vegetables): Represents the frequency of eating vegetables.
- FCVC (Frequency of consumption of high-calorie food): Represents the frequency of consuming high-calorie food.
- NCP (Number of main meals per day): Indicates the number of main meals the individual has per day.
- CAEC (Consumption of food between meals): Represents the consumption of food between meals.

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- SMOKE: Indicates whether the individual smokes.
- CH2O (Daily water consumption): Represents the daily water consumption of the individual.
- SCC (Caloric intake monitoring): Indicates whether the individual monitors their caloric intake.
- FAF (Physical activity frequency): Represents the frequency of physical activity.
- TUE (Time using technology devices): Represents the time spent using technology devices.
- CALC (Consumption of alcohol): Represents the consumption of alcohol.
- MTRANS (Transportation used): Represents the mode of transportation used by the individual.
- NObeyesdad (Obesity Level): Represents the obesity level of the individual, which is the target variable.



Machine Learning Approach for Prediction of Obesity Levels based

Fig 3: Home Page

The homepage of this "Obesity Prediction" web application features a navigation bar with buttons for "Home," "Wellness Manager," "Wellness Seeker," "New Signup," "About Obesity," and "Aboutdataset," indicating different sections and user roles within the platform. The presence of "Wellness Manager" and "Wellness Seeker" suggests distinct user interfaces, functionalities tailored to different user types, while "New Signup" allows new users to join, and "About Obesity" and "Aboutdataset" likely provide informational content about the topic and the data used for prediction.



Home	Wellness Manager	Wellness Seeker	New Signup	About Obesity	Aboutdataset
	Log	gin as Welln	ess Seeke	r	
	Usern	ame			
	Enter	Username			
	Passw	ord			
	Enter	rassworu		3	
		log	in	9	

Fig 4 Admin Login page

This login form for "Wellness Seekers" has fields for username and password, plus a "login" button. When submitted to a Django backend, the entered details are sent for authentication. Django's authentication system verifies these credentials. Successful login creates a session, granting access; failed attempts usually redisplay the form.

Load Data	Train I	Model	User H	istory	User List	Logout
				11	1915	
	Model	Accuracy	Precision	Recall	F1-Score	
o ExtraTre	esClassifier	0.953003	0.954651	0.9 <mark>53003</mark>	0.953567	
1 VotingCl	assifier	0.937337	0.938100	0.937337	0.936994	

Fig 5: Model Training

This Figure presents the performance evaluation of two machine learning models: Extra Trees Classifier and Voting Classifier. For each model, it reports four key metrics: Accuracy, Precision, Recall, and F1-Score. The Extra Trees Classifier shows a slightly higher performance across all metrics, with an Accuracy of 0.953003, Precision of 0.954651, Recall of 0.953003, and an F1-Score of 0.953567. The Voting Classifier achieves an Accuracy of 0.937337, Precision of 0.938100, Recall of 0.937337, and an F1-Score of 0.936994. These metrics suggest that both models perform well, but the Extra Trees Classifier demonstrates a marginally better ability to correctly classify instances (Accuracy), identify

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relevant instances (Precision), find all relevant instances (Recall), and achieve a balanced measure of precision and recall (F1-Score) on the evaluated dataset.

Pre	dictio	n of Obe	esity Lev	vels		
Gender:	v	Age:				
Height (m):		Weight (kg):				
Family History with Overweight:		Frequent Co	nsumption of I	ligh Calorie Fo	boo	
Yes	٠	(FAVC): Yes			-	
Frequency of Consumption of Vege	tables	Number of M	lain Meals (NC	P):		
(ECVC):						

Fig 6: Input For Predicting Obesity Level

This Figure displays an input form designed for "Prediction of Obesity Levels." It consists of several fields to collect relevant information from a user. These fields include "Gender" (with a dropdown likely offering options like Male/Female), "Age" (an input field for numerical value), "Height (m)," "Weight (kg)," "Family History with Overweight" (a dropdown with "Yes" selected), "Frequent Consumption of High Calorie Food (FAVC)" (a dropdown with "Yes" selected), "Frequency of Consumption of Vegetables (FCVC)" (a dropdown with "1" selected), "Number of Main Meals (NCP)" (a dropdown with "1" selected), "Consumption of Food Between Meals (CAEC)" (likely a dropdown with options), and "Smoking Habit" (likely another dropdown). This form gathers personal and lifestyle data that would likely be used by a machine learning model in the backend to predict the user's obesity level.

Home	Check Obesity Level	Factors	Logout
Predicted output	as : Normal	Weight	t
Goal: Maintain a balanced diet a Foods to Include	and prevent weight gain.		
Protein sources: chicken, fish, egg	, tofa.		
Whole grains: oats, brown rice, ga	inoa.		
Fiber-rich vegetables and fruits.			
Foods to Avoid			
Buffer I and a second starts on	CRAS PAGET.		

Fig 7: Predicted output

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This image displays the predicted output of the obesity level prediction system. The text "Predicted output as : Normal_Weight" indicates the system's assessment of the user's weight category based on the input data. Following this prediction, personalized dietary recommendations are provided, framed around the goal of maintaining a balanced diet and preventing weight gain. The "Foods to Include" section suggests incorporating protein sources like chicken, fish, eggs, and tofu, whole grains such as oats, brown rice, and quinoa, as well as fiber-rich vegetables and fruits. Conversely, the "Foods to Avoid" section advises limiting refined carbs, processed foods, and excess sugar. This output provides both a weight status prediction and actionable dietary guidance tailored to maintaining a normal weight.

Model	Accuracy (%)	Precision	Recall	F1-score
Voting Classifier	0.93	0.93	0.93	0.93
ETC model	0.95	0.95	0.95	0.95

Table 1: Performance comparison of existing and proposed ML models.

For the Voting Classifier model:

- The Accuracy is 0.93, indicating the accuracy between the actual and predicted values
- The Precision is 0.93, suggesting that, on average Precision between the actual and predicted values.
- The Recall is 0.93, suggesting that, on average Recall between the actual and predicted values.
- The F1-score is 0.93, representing the average F1-score between the actual and predicted values.

For the Extra Tree Classifier model:

- The Accuracy is 0.95, indicating the accuracy between the actual and predicted values.
- The Precision is 0.95, suggesting that, on average Precision between the actual and predicted values.
- The Recall is 0.95, suggesting that, on average Recall between the actual and predicted values.
- The F1-score is 0.95, representing the average F1-score between the actual and predicted values.

5. CONCLUSION

In conclusion, this research has delved into the intricate link between eating habits and obesity, leveraging the power of machine learning (ML) to predict obesity levels. The utilization of diverse demographic information and dietary patterns within a comprehensive dataset has allowed for a nuanced exploration of this complex health issue. Through the application of various ML algorithms such as Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, predictive models have been crafted, revealing the potential of data-driven methodologies in understanding and addressing obesity. The evaluation of model performance using metrics like accuracy, precision, recall,

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and F1-score has provided a robust assessment of the predictive capabilities of these ML algorithms. The findings indicate promising outcomes, with certain algorithms showcasing superior accuracy and reliability in forecasting obesity levels based on eating habits. Moreover, the incorporation of feature selection methods has unveiled the most influential dietary factors contributing to obesity. This not only enhances the interpretability of the models but also provides actionable insights for targeted interventions. The identification of specific food groups and consumption patterns strongly associated with obesity adds a layer of granularity, paving the way for personalized dietary recommendations and more effective strategies to combat the obesity epidemic.

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