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Examination and Evaluation of Obesity Risk Factors with Explainable Artificial Intelligence

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ABSTRACT There is an increasing need for effective methods for the detection and management of obesity, which is an important public health problem worldwide and is critical for the sustainability of health systems. This study examines the effectiveness of data preprocessing and machine learning techniques in detecting obesity. Data preprocessing steps, including the removal of unnecessary data, handling missing values, and addressing data imbalance, are necessary to enhance the accuracy of machine learning algorithms. In this study, data preprocessing steps were applied to an obesity dataset to make it suitable for machine learning. Using a dataset of 2111 patients, this study evaluates the effectiveness of machine learning techniques in detecting obesity. Following the completion of data preprocessing, obesity was identified using various machine learning algorithms, including Decision Tree Classification, Random Forest Classification, Naive Bayes Classification, KNN, and XGBoosting, and their performances were compared. According to the results, the XGBoosting algorithm exhibited the highest accuracy (0.92), precision, recall, and F1-score values. Explainable Artificial Intelligence (XAI) techniques, such as SHAP and InterpretML, were employed to understand the effects of obesity parameters and determine which parameters have a greater impact on obesity. By visualizing and analyzing the effects of obesity parameters, these techniques facilitated the identification of significant parameters in obesity detection. The findings demonstrate that the XGBoosting algorithm outperforms other algorithms in detecting obesity. Furthermore, XAI techniques play a crucial role in comprehending obesity parameters. Specifically, a family history of obesity and factors like FCVC and CAEC appear to have more significant effects compared to others.

KEYWORDS
Explainable AI
Obesity detection
Machine learning
XGBoost
InterpretML

INTRODUCTION

Obesity has become a significant global health issue, emphasizing the importance of understanding factors associated with obesity (Bray 2003). Fundamental physical attributes such as weight, height, and age have been studied for their effects on obesity (Tariq Aziz 2024). Traditional and artificial intelligence-based methods are employed for obesity detection, with this section focusing on the methods identified by experts and the role of artificial intelligence in obesity detection. The accurate processing and organization of obesity-related data significantly impact the success of machine learning models. Hence, this section will delve into data preprocessing steps and techniques as a crucial aspect. Machine learning models serve as effective tools for predicting obesity, with different models tested on the obesity dataset to analyze the obtained results. XGBoost, a widely used machine learning algorithm, plays a crucial role in obesity prediction. This section will focus on its application in the obesity dataset. Evaluating the results of the XGBoost model and applying explainable artificial intelligence techniques (SHAP, InterpretML) are essential for assessing the accuracy and reliability of the obtained results.

Sejong Oh (2021) conducted a study on explainable machine learning models for glaucoma diagnosis and interpretation. The aim was to develop a machine learning prediction model for diagnosing glaucoma and an explanation system for specific predictions. The study tested support vector machine, C5.0, random

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forest, and XGBoost algorithms for the prediction model. The proposed framework combines global and local interpretable methods, enhancing the transparency of complex models. This framework provides insight into judgments from complex models, guiding treatment strategies, and improving the prognosis of hepatitis patients (Sejong Oh 2021).

Junfeng Peng (2021) explored black-box models such as eXtreme Gradient Boosting (XGBoost), support vector machine (SVM), and random forests (RF). The proposed framework combining global and local interpretable methods improves the transparency of complex models and provides insight into judgments from the complex models, thereby guiding treatment strategies and improving the prognosis of hepatitis patients (Junfeng Peng 2021). Jungsu Park (2022) explored the interpretation of ensemble learning to predict water quality using explainable artificial intelligence. They developed an XGBoost ensemble machine learning model from eighteen input variables to predict Chl-a concentration. Their study showed that the model exhibited the most stable performance when the priority of input variables was determined by SHAP (Jungsu Park 2022).

A. Moore (2022) compared two machine learning methods, XGBoost and logistic regression, in predicting the risk of myocardial infarction (MI). Their findings suggest a future where Explainable AI may bridge the gap between medicine and data science (A. Moore 2022). Jaishree Meena (2022) aimed to find potential diagnostic biomarkers for SCC by applying eXplainable Artificial Intelligence (XAI) on XGBoost machine learning models trained on binary classification datasets. After successfully incorporating SHAP values into the ML models, they identified 23 significant genes associated with the progression of SCC (Jaishree Meena 2022).

B. Kui (2022) identified the most critical factors and their contribution to prediction using SHapley Additive exPlanations (SHAP). They developed a free and easy-to-use web application in the Streamlit Python-based framework for explanation and confidence estimation (B. Kui 2022). Chang Hu (2022) studied the application of interpretable machine learning for early prediction of prognosis in acute kidney injury. Their findings highlight Glasgow Coma Scale (GCS), blood urea nitrogen, cumulative urine output on Day 1, and age as the top 4 most important variables contributing to the XGBoost model (Chang Hu 2022).

Hafsa Binte Kibria (2022) proposed an ensemble approach for predicting diabetes mellitus using a soft voting classifier with explainable AI. They provided global and local explanations using Shapley additive explanations (SHAP) to aid physicians in understanding model predictions (Hafsa Binte Kibria 2022). Artificial intelligence (AI) has diversified into various healthcare applications, such as health services management, predictive medicine, clinical decision-making, and patient data and diagnostics. Hui Wen Loh (2022) aimed to draw attention from the XAI research community to areas of healthcare requiring more focus (Hui Wen Loh 2022). Isfafuzzaman Tasin (2022) developed an automatic diabetes prediction system using various machine learning techniques. They implemented an explainable AI approach with LIME and SHAP frameworks to understand how the model predicts final results (Isfafuzzaman Tasin 2022).

The introduction provides a comprehensive overview of the significance and challenges of utilizing machine learning models, particularly in healthcare. The literature review section delves into various studies that have explored the application of explainable artificial intelligence (XAI) techniques to enhance the interpretability of machine learning models in medical diagnosis and prognosis. However, this study aims to contribute to the existing body of knowledge by offering a unique perspective on the interpretability of machine learning models. Specifically, we focus on the importance of moving away from black-box models and instead emphasize the utilization of techniques that enable us to understand the contributions of input parameters to output parameters. By employing methods such as SHapley Additive exPlanations (SHAP), we can gain insights into the extent to which each input parameter influences the output parameter. This approach not only enhances the transparency of the model but also facilitates the development of more robust and reliable predictive models in healthcare. In the Materials and Methods section, a comprehensive description of the dataset was provided, along with elucidation on the operational principles of the employed machine learning algorithms and the functioning of the utilized explainable artificial intelligence algorithms. The Results section will present the obtained outcomes, while in the Discussion section, an overall overview of the study will be provided. The coherence and scope of the obtained results will be discussed, along with an examination of how the study may inspire further research endeavors.

MATERIALS AND METHODS

Dataset

The dataset used in this study contains a range of demographic and physiological features related to obesity. The features of the dataset include: The dataset initially contained missing or conflicting data. Therefore, preprocessing steps were applied to prepare the dataset. The structure and characteristics of the dataset were examined to identify missing or abnormal values. The "NObeyesdad" feature, which was unnecessary for analysis, was removed from the dataset. Categorical values in some features were converted to numerical values. Body Mass Index (BMI) was calculated, and participants were assigned to six different obesity categories based on their BMI. Data types of some features were appropriately converted. Obesity categories were converted to numerical values to prepare for analysis. With these preprocessing steps, the dataset was made suitable for analysis and obtaining results.

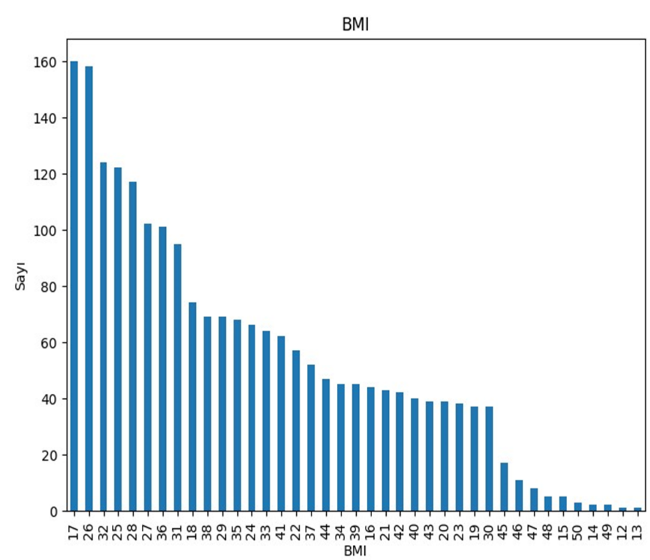

Figure 1 Generated BMI column values

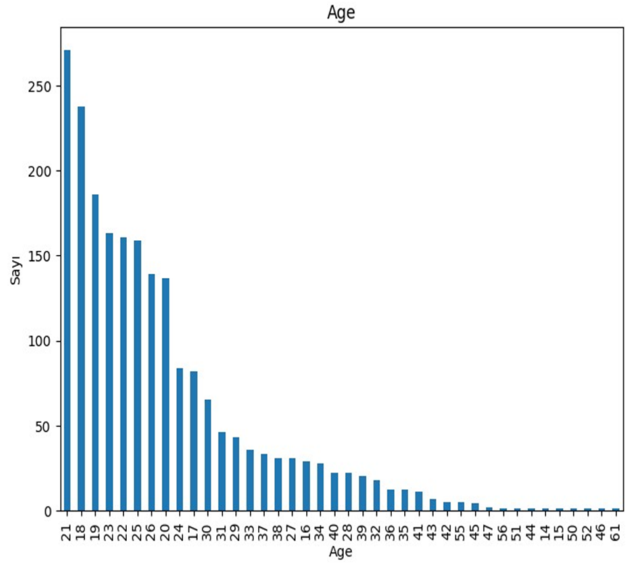

Figure 2 Age values

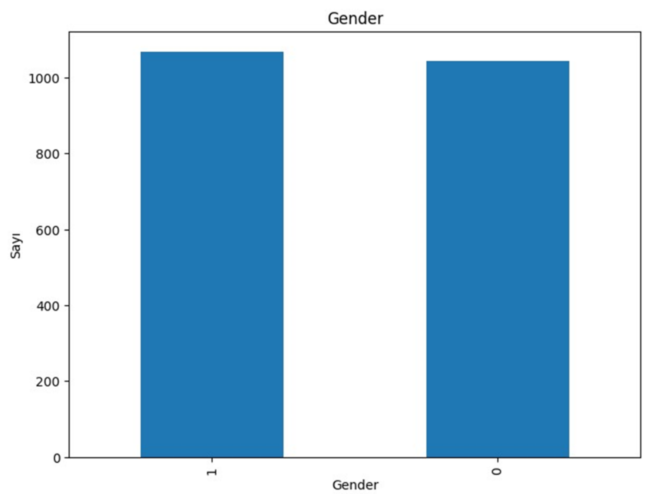

Figure 3 Gender values

Machine Learning

Decision Tree Classification Decision Tree Classification is a machine learning method commonly used for classification problems. A decision tree is widely used for understanding complex relationships in a dataset and making predictions (Charbuty 2021). There are multiple algorithms available for implementing decision trees. C4.5 can handle both categorical and numerical features. It utilizes an advanced algorithm to optimize information gain. Entropy is a concept that measures uncertainty in a system. In decision trees, entropy is used to measure the homogeneity or heterogeneity of the distribution of data points at a node. A lower entropy value indicates a more homogeneous data distribution. Entropy of P is given by (Hssina 2014).

$$\text{Entropy}(X) = -\sum_{x} p(x) \cdot \log_2(p(x)) \tag{1}$$

In the formula, $p(x)$ represents the probability of randomly selecting an element from class x.

Random Forest Classification Random Forest classification is a machine learning technique where multiple decision trees are assembled. Each decision tree is trained on randomly sampled subsets of the data, and then these trees are aggregated to form a forest. Each tree is split using randomly selected features, ensuring diversity. Compared to a single decision tree, Random Forests offer better generalization and higher accuracy. This method is commonly used for classification problems and tends to perform well on high-dimensional and complex datasets (Boateng 2020).

Naive Bayes Classification Naive Bayes classifiers are a family of models based on Bayes' Theorem (Berrar 2019). Bayes' Theorem is given by:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{2}$$

The expression $P(A|B)$ represents the probability of event A occurring given that event B has occurred. $P(B|A)$, on the other hand, represents the probability of event B occurring given that event A has occurred. $P(A)$ denotes the marginal probability of event A, i.e., the probability of event A occurring when event B is ignored. Similarly, $P(B)$ denotes the marginal probability of event B, i.e., the probability of event B occurring when event A is ignored.

Naive Bayes classification is a machine learning algorithm used to predict the probability of an instance belonging to a certain class. It assumes independence among features to determine the class of an instance, hence the term 'naive.' The Naive Bayes classifier utilizes the relationships between features based on training data to compute the probability of an instance belonging to a given class. As a result, this algorithm is often preferred as a simple yet effective classification solution and yields successful results, particularly in areas such as text classification. Naive Bayes classification can work swiftly and efficiently in high-dimensional datasets and real-time applications (Jadhav 2016).

K-Nearest Neighbors K-Nearest Neighbors (KNN) is a simple and effective classification algorithm that utilizes the labels of neighboring observations to determine the class of an observation. Its fundamental principle is to use the labels of the k nearest neighbors of a new observation to determine its class. The KNN algorithm employs similarity measures between examples in a pre-labeled training dataset. The similarity between observations is typically calculated using Euclidean, Manhattan, or Minkowski distance measures. While the algorithm is commonly used for classifying data points, it can also be applied to regression problems. However, the computational intensity and memory requirements of KNN can be a disadvantage for large datasets.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{3}$$

$$\sum_{i=1}^{k}|x_i - y_i| \tag{4}$$

$$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q} \tag{5}$$

$$d(x,y) = \sqrt{\frac{1}{2}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{6}$$

XGBoosting XGBoost is a leading library built upon a machine learning technique called gradient tree boosting. Gradient tree boosting is a powerful technique that captures complex data dependencies, resulting in successful outcomes across various datasets. XGBoost stands out with the following features (Chen 2016):

- **High Prediction Power:** XGBoost has the ability to generate accurate and precise predictions, ensuring high accuracy in its forecasts.
- **Preventing Overfitting:** XGBoost employs various techniques to prevent overfitting, making it a model with high generalization ability.
- **Handling Missing Data:** XGBoost excels in handling missing data, extracting meaningful insights even from incomplete datasets.
- **Fast Processing:** XGBoost operates swiftly due to its optimized algorithms, making it suitable for processing large datasets efficiently.

XGBoost leverages software and hardware optimization techniques to achieve superior results with fewer resources. This capability has positioned XGBoost as one of the top decision tree algorithms.

Explainable Artificial Intelligence

SHAP SHAP represents an Explainable AI (XAI) methodology, employing Shapley values derived from game theory to offer intelligible insights into the pivotal and influential factors influencing the model's forecasts (Zhang 2023). Shapley values originate from cooperative game theory and serve as a concept that impartially gauges a player's contribution. SHAP furnishes a structure for comprehending the mechanism by which a model generates its predictions leveraging these values (Feng 2021).

InterpretML InterpretML (Machine Learning Interpretation) encompasses a range of techniques and methodologies aimed at enhancing the comprehensibility of machine learning model decision processes. It is particularly imperative to elucidate the factors underpinning a specific prediction or classification and to elucidate the rationale behind a model's attainment of a particular outcome. Among the pivotal techniques within InterpretML is the analysis of "Feature Importance". This method is employed to discern the most impactful features in a model's predictions, thereby facilitating an understanding of which features exert a greater influence on the model's outputs. Additionally, methodologies such as "Partial Dependence Plots" and "SHAP Values" are utilized to visually represent and expound upon the influence of specific features on prediction outcomes. These approaches serve as essential tools for fostering a deeper comprehension of model behavior (Nori 2019).

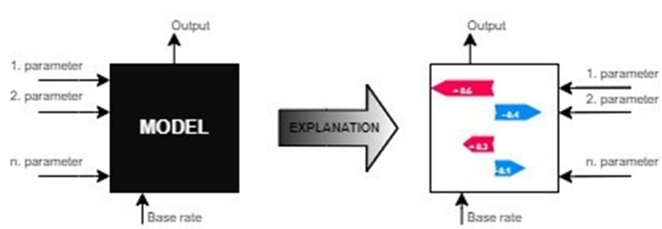

Figure 4 SHAP Structure

RESULTS AND DISCUSSION

The dataset used for the machine learning updates first went through a few pre-processing steps. First, the "NObeyesdad" column was removed from the dataset because it could not be used in model training. Then, some features in the categories were coded as "yes" and "no" in the data set. These features had to be converted into digital values in order to train the model correctly. This conversion is used to introduce properties such as family history with overweight, FAVC, SMOKE, and SCC. Additionally, categorical features such as "Gender", "CAEC", "CALC" and "MTRANS" were converted into digital values through the processing of the categories. Body mass index (BMI) was calculated based on the "weight" and "height" features in the dataset. The people were then divided into obesity categories (underweight, normal, overweight, obesity I, obesity II, obesity III) based on the recorded BMI values. These categories were used to determine tolerance to specific BMI ranges and levels of obesity.

Obesity categories were converted into social digital values during model training. This transformation assigns a value of 0 to the categories "Underweight," "Normal," and "Overweight," while assigning a value of 1 to the categories "Obesity I," "Obesity II," and "Obesity III." This transformation was performed to increase the pores of the model.

Various machine learning models have been applied in machine learning, such as Decision Tree Classification, Random Forest Classification, Naive Bayes Classification, KNN, and XGBoosting. The performance of each model was evaluated using Precision, Recall, F1-Score, and Accuracy metrics. Precision, Recall, F1-Score, and Accuracy are commonly used metrics to evaluate the performance of machine learning models. Precision measures how many of the examples the model classifies as positive are actually positive, while Recall measures how much of the true positive examples are correctly classified. F1-Score is the harmonic average of Precision and Recall and provides a balanced measure of performance. Accuracy shows the proportion of correctly classified samples. The results obtained are presented in the table below:

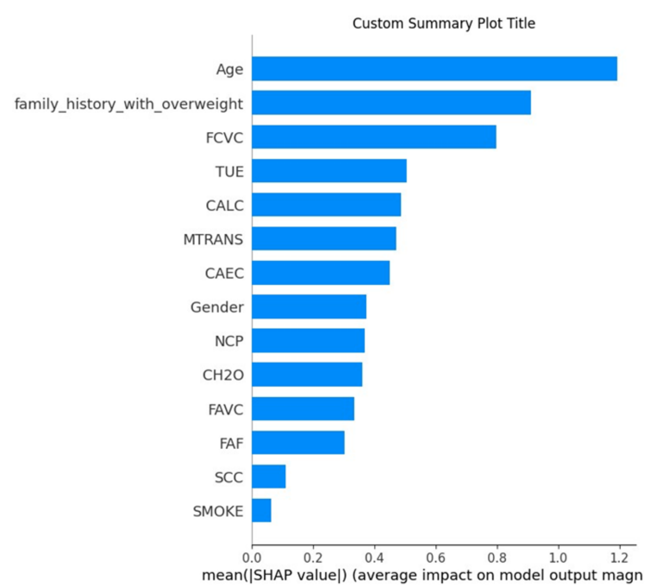

Figure 5 Extracting features with SHAP

Table 1 Classification Metrics

Model	Precision	Recall	F1-Score	Accuracy
XGBoosting	0.92	0.92	0.92	0.92
Random Forest Classification	0.91	0.91	0.91	0.91
Decision Tree Classification	0.89	0.89	0.89	0.89
KNN	0.87	0.87	0.87	0.87
Naive Bayes Classification	0.82	0.78	0.78	0.78

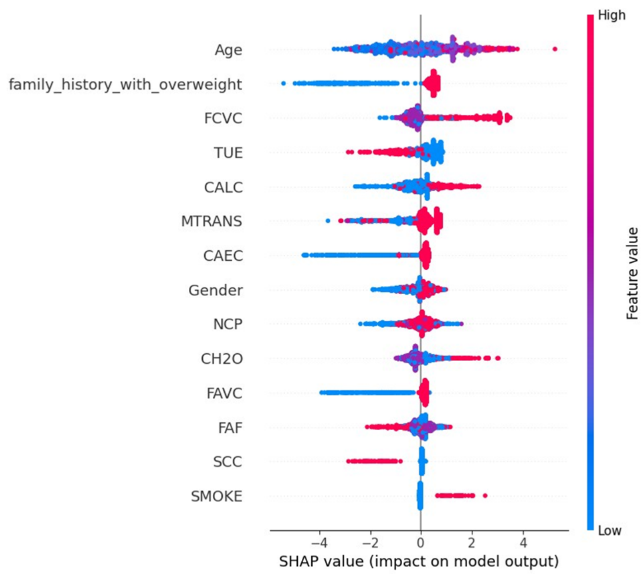

Figure 6 SHAP Summary Plot

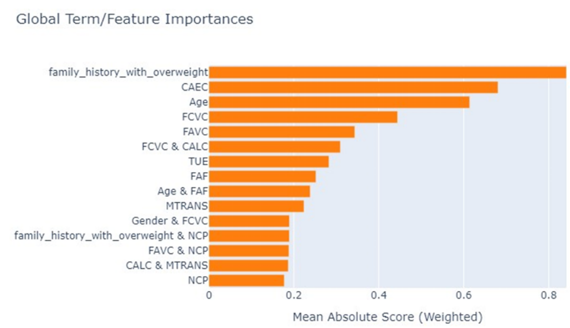

Figure 7 The overall impact of features on the model's predictions

According to the results, the XGBoosting model achieved the highest Precision, Recall, F1-Score, and Accuracy values. Therefore, it has been determined as the most effective model for classifying data.

After the machine learning phase, factors influencing obesity risk were examined using SHAP analysis. According to the analysis results, the effect of age on obesity was found to be significant, with obesity risk increasing as age increases. Additionally, it was observed that individuals with a family history of obesity increase their own obesity risk, emphasizing the role of genetic factors. Low consumption of vegetables was found to be associated with obesity risk, highlighting the critical role of regular vegetable consumption in preventing obesity. The widespread use of technological devices was found to increase obesity risk, underscoring the importance of physical activity in obesity prevention. Furthermore, monitoring daily caloric intake and utilizing active transportation modes were identified as factors that reduce obesity risk. Snacking habits were found to be associated with obesity risk, emphasizing the importance of regular and balanced meal planning in obesity prevention. Lastly, the effect of gender on obesity was found to be related to hormonal differences and lifestyle factors, with the female gender increasing obesity risk. These findings contribute significantly to understanding the complex etiology of obesity and developing effective preventive strategies.

InterpretML In the graph interpretation, the prominent features of the model were family history and overweight, CAEC, and age. These findings emphasize that health status plays an important role in explaining obesity risk. Furthermore, the impact of age on obesity needs to be considered. Other important characteristics indicated in the graph were also observed to contribute to the model's predictions. However, it was noted that the increase of NCP was low. These results allow health professionals to develop more effective solutions for the assessment and prevention of obesity risk. In conclusion, these findings presented in the graph provide an important resource for evaluating the presentation of the model and guiding health policies.

CONCLUSION

In this study, it was aimed to determine the parameters effective in determining obesity and to measure these weights. Various parameters including lifestyle factors such as gender, age, height, weight, and family history of obesity were analyzed using a dataset of 2111 patients. Machine learning techniques, specifically XGBoost and Explainable Intelligence Machine algorithms, were employed to train the dataset. Demonstrated a successful detection of obesity with an accuracy of 0.917 using XGBoost. Additionally, effective parameters and their weights in classification were determined using explainable artificial intelligence (XAI) and InterpretML methods. In conclusion, this study contributes to the understanding of factors related to obesity and the development of effective treatment strategies. The results highlight the importance of further integrating these findings into clinical practice and obesity management. Future research should focus on exploring how these findings can be effectively applied in clinical settings.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

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