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Explainable artificial intelligence for investigating the effect of lifestyle factors on obesity

Tarek Khater [a], Hissam Tawfik [a,*], Balbir Singh [b]

[a] Electrical Engineering Department, University of Sharjah, Sharjah, United Arab Emirates
[b] School of Built Environment Engineering and Computing, Leeds Beckett University, United Kingdom

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ABSTRACT

Obesity is a critical health issue associated with severe medical conditions. To enhance public health and well-being, early prediction of obesity risk is crucial. This study introduces an innovative approach to predicting obesity levels using explainable artificial intelligence, focusing on lifestyle factors rather than traditional BMI measures. Our best-performing machine learning model, free from BMI parameters, achieved 86.5% accuracy using the Random Forest algorithm. Explainability techniques, including SHAP, PDP and feature importance are employed to gain insights into lifestyle factors' impact on obesity. Key findings indicate the importance of meal frequency and technology usage. This work demonstrates the significance of lifestyle factors in obesity risk and the power of model-agnostic methods to uncover these relationships.

1. Introduction

Obesity is widely recognized as a significant determinant of human health (Ataey et al., 2020, Biswas et al., 2017) and one of the most important factors affecting human health and associated with numerous critical health conditions, such as cardiac disease, type 2 diabetes, high blood pressure, and certain types of cancer. According to a World Health Organization (WHO) study published in 2022, (World health organization obesity and overweight 2022), the global prevalence of obesity exceeds 1 billion individuals, encompassing approximately 650 million adults, 340 million adolescents, and 39 million children. The prevalence of overweight and obesity continues to increase steadily, and projections from the World Health Organization (WHO) (World health organization obesity and overweight 2022) indicate that by 2025, approximately 167 million individuals, encompassing both adults and children, will face compromised health due to excess weight. Furthermore, studies suggest that by 2030 (Kolahi et al., 2018), the number of overweight individuals is anticipated to exceed 2.16 billion, with 1.12 billion classified as obese. For this reason, obesity and overweight (Guh et al., 2009) have been recognized as important risk factors for a variety of health disorders in epidemiological research. The body mass index (BMI) serves as the principal measure utilized to assess whether an individual's weight falls within the range of normal, overweight, or obese. The BMI is the ratio of a person's body mass in kilograms to the square of their height in meters. In adults (Singh and Tawfik, 2020), BMIs less than 18 kg/m2 are considered underweight, those between 18 and 25 kg/m2 are considered normal weight, and those greater than 25 and 30 kg/m2 are considered overweight and obese, respectively (W. H. Organization 2000). In many nations, the rising incidence of obesity and its associated mortality endangers public health. Furthermore, it has a negative impact on people's quality of life and places a financial burden on society (Dai et al., 2020, Tremmel et al., 2017).

1.1. Lifestyle factors

Some genetic and lifestyle variables (Safaei et al., 2021) influence an individual's risk of becoming obese as an adult; consequently, a considerable cohort of obesity reported in specific geographical locations and contexts also indicate the effect of environmental and socio-economic factors in "obesogenic" settings. Environmental and lifestyle factors (Marti et al., 2004) that encourage excessive calorie consumption and sedentary behavior are known to generate a positive energy balance, which leads to weight gain. The expansion of food systems on a global scale (Chooi et al., 2019), as evidenced by increased food processing and affordability, has contributed significantly to the rise of the obesity epidemic.

Swinburn et al. (Swinburn et al., 2011) attributed to the promotion of passive overconsumption of beverages, energy-dense, and

* Corresponding author.
E-mail address: htawfik@sharjah.ac.ae (H. Tawfik).

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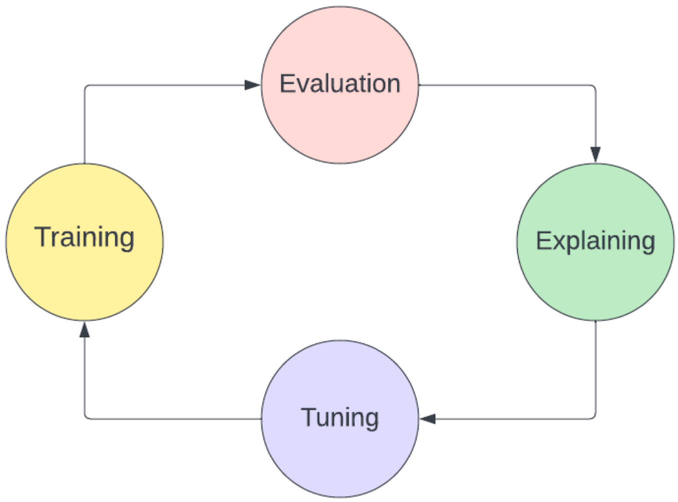

Fig. 1. The complete process of building ML model

nutrient-poor foods. Additionally, the modernization of lifestyles, which often leads to reduced physical activity levels, is likely another factor involved in the prevalence of obesity (Ladabaum et al., 2014). Lifestyle changes, such as bad dietary pattern, lack of exercise, and sociocultural and socioeconomic transformations, are considered the major reasons for the rise in obesity and overweight (Mokdad et al., 2016). Diet, lack of physical exercise, sleep, stress, alcohol, and smoking all are examples of lifestyle factors that disturb physiology and cause illness (Ahmad et al., 2019).

1.2. Machine learning and Explainable artificial intelligence

Machine learning (ML) is a distinct area within broader realm of artificial intelligence, focused on creating algorithms and statistical models that empower computers to enhance their performance through iterative learning. By leveraging data, these algorithms and models are designed to autonomously acquire knowledge and improve their ability to make predictions or decisions, all without the need for explicit programming instructions. Supervised Learning (Thampi and Interpretable, 2022) is a type of ML system in which the goal is to map the input (features) to their corresponding outputs (targets) using examples of input-output pairs. It necessitates labeled training data. The well-known supervised ML algorithms include linear and support vector machine (SVM), logistic regression, XG-boost, decision tree, Random Forest, K-nearest neighbor (KNN), and artificial neural networks (ANN) (Esen et al., 2017). These algorithms are considered "white box" models such as the linear and logistic models and some are "black box" models, for example, ANN, SVM, and Random forest. The term "black box" (Loyola-Gonzalez, 2019) refers to all ML models that are (from a mathematical standpoint) extremely difficult to explain and understand by specialists in practical fields. Experts in ML must ideally comprehend the black-box-based model to be used since, in most cases, these models must be adjusted to produce correct results. Therefore, explainable artificial intelligence (XAI) is utilized to provide interpretations for the model behavior and try to convert black box models to white ones (Hulsen, 2023). XAI is a collection of methodologies and techniques for describing the outcomes of ML model construction in a way that people can comprehend (Gianfagna and Di Cecco, 2021).

Recently, ML has emerged as a promising approach to developing automated and objective weight-level classification models (Khater et al., 2023). These models are trained to classify the weight levels into, for instance, underweight normal weight, overweight, and obesity. Later, these models are evaluated to recognize their performance. Finally, the outcome in terms of the performance of the model needs to be explained. Here, is the role of explainable artificial intelligence (XAI). The simple block diagram in Fig. 1 shows the complete process of building an ML model.

The key contributions of this research:

- Investigating the impact of lifestyle factors on obesity is a new research rea with the ultimate goal of advancing public health and fostering betterinformed strategies for the prevention and management of obesity.
- Our best-performing Machine Learning (ML) model, designed to operate without relying on weight, height, or BMI parameters, achieved an impressive 79% accuracy using the Random Forest algorithm with the "oneversus-all" technique. This high accuracy underscores the effectiveness and reliability of our innovative approach.
- A distinguishing feature of this research is the application of explainable artificial intelligence methods, such as permutation importance, partial dependence plots, and Shapley Additive exPlanations (SHAP). These techniques offer valuable insights into the influence of lifestyle factors on obesity levels, enhancing the interpretability of ML outcomes. For example, through SHAP local investigations, we have uncovered vital insights into predicting normal weight using an ML model. Notably, the number of main meals consumed daily emerged as a pivotal factor, with a crucial threshold of 1.2 meals per day for accurate classification. Additionally, our research has highlighted the impact of technology usage on obesity development, as revealed by local SHAP analyses, elucidating the connection between technology and increased obesity risk. Global SHAP explanations indicate that the consumption of food between meals is directly proportional to the ML model's obesity class predictions.

In summary, our findings emphasize the substantial influence of lifestyle factors on obesity risk, transcending the limitations of conventional BMI-based assessments. Moreover, this work showcases the potential of model-agnostic methods in unraveling the complex relationships between various lifestyle factors and obesity classification, ultimately contributing to a deeper understanding of this critical public health issue.

This paper aims to develop an ML model that can accurately classify weight levels based on various lifestyle factors while ensuring the interpretability of the model's predictions. The primary aim is to construct a model that demonstrates robust predictive performance and facilitates a clear understanding of the underlying relationships between lifestyle factors and weight classification outcomes. Key lifestyle determinants, such as dietary habits, physical activity levels, sleep patterns, and other behavioral factors, will be systematically analyzed to elucidate their influence on weight status. By prioritizing model interpretability, this research seeks to provide actionable insights that can guide healthcare professionals and individuals in identifying specific lifestyle modifications that contribute to achieving and maintaining optimal weight levels.

The subsequent sections of this paper are structured as follows: Section 2 discusses the related works. The XAI methods are explained in Section 3. The dataset and the methodology are discussed in Section 5. Finally, the results of the study are presented in Section 6 followed by a discussion of key conclusions and future work drawn from the research.

2. Related works

The direction for performing this literature review is not to search for the best accuracy to classify or predict obesity, but to know according to what features they perform the ML task. The novelty of this research is based on the utilization of lifestyle factors rather than BMI values in order to provide a better comprehension of the lifestyle variable that influences the model's predictions of weight levels, as well as to identify the most critical features for the classification task.

A software method based on the decision tree algorithm was created by Correa et al. (De-La-Hoz-Correa et al., 2019) to evaluate the level of obesity based on variables such as weight, height, diet, and lifestyle. It could be countered, though, that the combination of height and weight can be enough to accurately predict and categorize obesity in any case. This is because the BMI directly linked to evaluating obesity is reflected by the combination of height and weight. The decision tree's precision rate was best, coming in at roughly 97.4%, and its true positive rate was 97.8%.

The model showed a 0.2% false positive rate. Consequently, the model was successful in predicting the patients' levels of obesity. Singh and Tawfik (Singh and Tawfik, 2020, Singh and Tawfik, 2019) developed a machine-learning model to estimate the likelihood that young individuals will become overweight or obese using data on childhood obesity from the UK data service. The risk that teens will become overweight or obese by the age of 14 is calculated using BMI measurements from children in years 3, 5, 7, and 11. In that study, a number of ML algorithms were assessed for their ability to correctly forecast persons' propensity to become overweight or obese. In a different investigation, Hera et al. (Siddiqui et al., 2020) investigated facial images as a weightmonitoring application and a diagnostic tool for obesity. For several face image datasets, various deep learning algorithms for estimating BMI were explored; DenseNet and ResNet outperformed other nets in terms of performance. Yamur et al.'s research (Efe et al., 2020) on social phobia, emotional eating, and parental perspectives in obese and lean adolescents looked at these topics. Obese adolescents reported higher mean scores for social anxiety and emotional eating compared to healthy adolescents. Xueqin et al.'s goal (Pang et al., 2019) was to learn more about and understand how childhood obesity develops. There is an urgent need for preventative strategies given the importance of lowering the prevalence of childhood obesity and the accompanying health issues. An ML algorithm called XG-boost was used to create a prediction model to forecast the likelihood of future obesity among young individuals, aiming to mitigate this concern obese in the future in order to solve this problem. Ahn et al. (Ahn et al., 2018) classified obesity using different clustering approaches and compared the results. In this study, the researchers looked for a fresh approach to AI classification that used the fewest possible body dimensions as input features. The results showed that among many classification techniques including Decision tree (DT), discriminant analysis (DA), neural network (NN), K-nearest neighbor (KNN), and support vector machine (SVM), the fuzzy rule-based system (FRBS) was determined to be the most acceptable methodology. It was found that FRBS was accurate when compared to other effective AI algorithms and DA.

Among Saudi teenagers between the ages of 14 and 19 years old, M Al-Hazzaa and colleagues (Al-Hazzaa et al., 2012) evaluated the relationships between obesity indicators and a variety of lifestyle factors, including physical activity, sedentary behaviors, and eating habits. In addition to measuring BMI, waist circumference, waistto-height ratio (WHtR), screen time (i.e. The duration dedicated to television viewing, video game playing, and computer usage), and dietary habits (i.e. frequency of food intake per week), the research involved administering a validated questionnaire to assess the level of physical exercises. The associations between obesity indicators and lifestyle factors were examined using logistic regression. According to the logistic regression analysis, being overweight or obese (as per BMI categories) or having abdominal obesity (as per WHtR categories) were both significantly and inversely proportional with high levels of vigorous physical activity, regularly consuming breakfast and vegetables, and limiting the intake of sugary beverages. To address childhood obesity, Carvalho et al. (de Moura Carvalho et al., 2018) created the mobile exercise game mission kid. The exergame is a smartphonebased digital game that requires kids to engage in physical activity. The results produced using a decision tree showed an average accuracy of recognition of the workouts equal to 91.52% for a range of 5 proposed exercises. According to this study, smartphones can be a vital weapon in the struggle against childhood obesity. In order to predict future trends in obesity, Gupta et al. (Gupta et al., 2022) created a deep-learning model that makes use of publicly available data on children's medical histories. They did this by using a big dataset of raw electronic health records from a major US pediatric health system. The system forecasts obesity among persons ages 3 to 20 using data from 1-3 years in the future. This study aims to define various weight levels initially based mostly on lifestyle characteristics rather than BMI, weight, height, or family history. This would therefore make it possible to employ interpretable ML models to examine how certain lifestyle factors affect the classification or prediction of various weight levels. To provide recommendations for reducing body fat mass in order to prevent diseases brought on by an unhealthy lifestyle, Ushikubo et al. (Ushikubo et al., 2016) conducted another study. Five male 20-year-old subjects who were not obese provided lifestyle time-series data that was used in the study. To extract the rules, inductive logic programming (ILP) was used. These guidelines combine an adequate protein intake with an adequate vitamin D intake and a low-fat diet.

Tharmin et al. (Thamrin et al., 2021) employed an innovative approach utilizing advanced ML techniques to predict obesity based on publicly available health data, specifically the Indonesian Basic Health Research (RISKESDAS). The objective of their study was to surpass conventional prediction models and pinpoint a comprehensive range of risk factors for adult obesity using readily available variables. To evaluate the performance of ML methods in detecting obesity, the authors compared three different approaches: Logistic Regression, Naive Bayes, and Classification and Regression Trees (CART). Additionally, they applied the Synthetic Minority Oversampling Technique (SMOTE) to address data imbalance. The findings indicated that the Logistic Regression method exhibited the highest performance, achieving an accuracy rate of approximately 72%. The authors reported that several factors were significantly associated with adult obesity, including marital status, location, age group, and educational background. sweet drinks consumption, grilled foods, seasoning powders, fatty/oily foods, soft/carbonated drinks, alcoholic drinks, preserved foods, mental-emotional disorders, physical activity, smoking, diagnosed hypertension, and fruit and vegetable consumption. By leveraging publicly available health data, the study sheds light on the predictive capabilities of ML algorithms in identifying risk factors and predicting obesity in adults. The authors' study (Lee et al., 2022) included a thorough examination of the genetic, epigenetic, and environmental components related to body mass index (BMI) and obesity. They used the generalized multifactor dimensionality reduction (GMDR) method to perform a combined genome-wide and epigenome-wide scan and analyze connections among a large number of SNPs, dietary and lifestyle factors, and DNA methylation sites (DMSs). The scientists used ML algorithms to predict people's obesity status in an independent test set after finding statistically relevant markers, such as genetic variations, epigenetic alterations, and nutritional variables. The area under the receiver operating characteristic curve (ROC-AUC), which gauges the models' accuracy, was used to evaluate the performance of the prediction models. The authors' study included a thorough examination of the genetic, epigenetic, and environmental components related to body mass index (BMI) and obesity. They used the generalized multifactor dimensionality reduction (GMDR) method to conduct a combined genome-wide and epigenome-wide scan and analyze connections among a large number of SNPs, DNA methylation sites (DMSs), and dietary and lifestyle factors. The scientists used ML algorithms to predict people's obesity status in an independent test set after finding statistically relevant markers, such as genetic variations, epigenetic alterations, and nutritional variables. The (ROC-AUC), which gauges the models' accuracy, was used to assess the performance of the prediction models.

In a new rule-based explainable machine learning approach that includes knowledge extraction, pre-processing, and functional validation, Anguita-Ruiz et al (Anguita-Ruiz et al., 2020) identified physiologically significant sequential patterns from longitudinal gene expression data in humans. They utilized in vivo temporal obtained

Table 1
The list of the selected articles and the ML techniques used to classify obesity

Research/Author	Methodology	Input types
Snekalatha et al, Biomed. Signal Process. Control (Snekhalatha and Sangamithirai, 2021)	Deep neural network (CNN)	Thermal images
B. Singh and H. Tawfik, 20th International Conference, Amsterdam (Singh and Tawfik, 2020)	ID3 algorithm, Naïve Bayes, Random Forest, and decision tree	BMI values
Hera et al. (Siddiqui et al., 2020), 19th IEEE International Conference on Machine Learning and Applications (ICMLA)	Deep neural network (CNN)	Facial images
Xueqin et al (Pang et al., 2019), 19th IEEE International Conference on Machine Learning and Applications (ICMLA)	XG-boost algorithm	Children's BMI
Eduardo et al (De-La-Hoz-Correa et al., 2019)	decision tree	Age, Gender, and lifestyle variables
Khalid Almohammadi (Almohammadi, 2020), International Journal of Online & Biomedical Engineering	type-2 fuzzy logic	BMI, family characteristics, unhealthy food choices, and lack of exercise
Lucas et al (de Moura Carvalho et al., 2018), springer	ML model embedded in mobile exergame	Children's movements
Casimiro Aday et al (Montañez et al., 2017), International Joint Conference on Neural Networks (IJCNN)	Gradient boosting, generalized linear models, SVM, random forests, and multilayer perceptron neural networks	Genetic variants, BMI, age, and gender
Mehak Gupta et al (Gupta et al., 2022), ACM Transactions on Computing for Healthcare (HEALTH)	Deep learning model	children's medical histories (EHR)
Sang Woo Kim et al (Kim et al., 2019), Plos One	2-DE-based proteomic experiments	Protein biomarkers
T. M. Alam et al (Alam et al., 2019), Informatics in Medicine Unlocked	Artificial neural network (ANN), Random Forest (RF), and K-means	BMI and glucose level
Yuhan Du et al (Du et al., 2022), Nature	a clinical decision support system (CDSS) based on explainable machine learning to predict gestational diabetes	blood biomarkers
Qinghan Xue et al (Xue et al., 2018), IEEE	Recurrent Neural Networks (RNNs)	Biomedical, behavioral, and activity data

through a long-term food intervention in 57 obese individuals to show the efficacy of our strategy (GSE77962). As validation populations, they made use of three different datasets that all had the same experimental layout. They confirmed a number of the recovered gene patterns as a consequence, proving the effectiveness of our approach to identifying biologically meaningful gene-gene temporal interactions. In healthcare diagnostics, smart biomarker detectors are utilized to monitor and pinpoint biomarker cutoff points. New bariatric studies have linked obesity to a heightened risk of breast cancer among women. This research suggests that proinflammatory cytokines and adipocytokines are responsible for the proliferation of adipose tissues and malignancy as a disease. The adipocytokines HOMA, adiponectin, leptin, and resistin, which have been recognized as the primary initiators of breast cancer in obese women during the past 20 years, are the focus of Muhammad Idrees and Ayesha Sohail's (Idrees and Sohail, 2022) research. They divided the concentrations of each adipokine into two categories: high and low. They investigated the relationship between each group's risk for breast cancer. Based on the patient's BMI and biomarker levels, the findings provide useful information for establishing precise therapy options for breast cancer patients. The health of persons receiving the vaccine is crucial to the equitable and efficient distribution of vaccines. It's critical to give vaccinations to elderly people, people over 65, and people with medical issues in order of importance.

Table 1 shows summarized related works for the use of ML to classify weight levels. In this table, in addition to the author's name, the methodology and the type of input features are mentioned as well.

In contrast to the existing studies, our research adopts a novel approach by focusing on lifestyle factors instead of relying on BMI values. This shift in perspective allows us to gain a deeper and more comprehensive understanding of the complex relationships between individual behaviors and obesity. By using lifestyle factors as predictive variables, not only valuable insights into the role of daily choices in obesity are provided but also an innovative methodology that can potentially revolutionize the way that the healthcare providers approach obesity research and prevention are offered.

3. Scenario example and dataset

The aim of this research is to develop a new model that incorporates lifestyle variables instead of relying solely on conventional BMI values (i.e., weight and height) to estimate the prevalence of obesity. Data was collected from individuals in Colombia, Peru, and Mexico, based on their physical attributes and dietary habits, and then labeled with the class variable "Obesity Level" (De-La-Hoz-Correa et al., 2019). The dataset included 17 features and 2111 records, and the classification of data was performed based on four categories ranging from insufficient weight to obesity. About 23% of the data was obtained directly from users through a web platform, while the remaining 77% was synthetically generated using the Weka tool and the synthetic minority over-sampling technique (SMOTE) filter. The attributes of the dataset included lifestyle variables such as calorie consumption per day, technology usage time, and frequency of physical activity, as well as factors related to eating habits, such as water and high-calorie food consumption, alcohol intake, and vegetable consumption. Additional important variables, including age, gender, weight, height, and family history of obesity, were also included. The lifestyle and eating habit factors were extracted from the dataset and used as input for the ML model. The ML model, along with its inputs and output, is shown in Fig 2. In addition, the information on the dataset variables is listed in table 2.

4. Methodology

To fulfill the objectives of this research, a robust and methodical approach will be employed, integrating a variety of machine learning (ML) algorithms to classify weight levels based on lifestyle factors. The methodology is delineated as follows:

Data Collection and Preprocessing: Initially, a comprehensive dataset will be compiled, encompassing a range of lifestyle factors including dietary intake, physical activity, and other pertinent behavioral attributes. The data will undergo stringent preprocessing, involving normalization, imputation of missing values, and feature selection, to ensure the integrity and suitability of the data for subsequent model development.

Model Development: A group of machine learning algorithms, such as decision trees, support vector machines (SVM), random forests, gradient boosting machines, and neural networks, will be implemented to construct models capable of classifying individuals into distinct weight categories (e.g., underweight, normal weight, overweight,

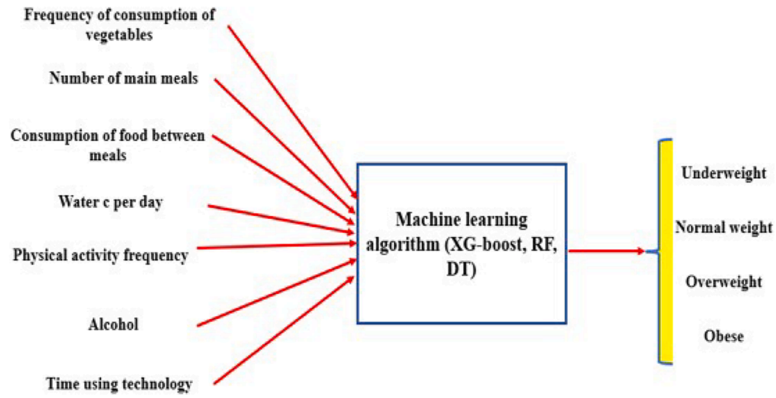

Fig. 2. Block Diagram of ML model for 4 classes

Table 2
The measurement scale for each feature

Inputs Features	Measurement scale
Frequent consumption of high caloric food (FAVC)	(Yes, No)
Frequency of consumption of vegetables (FCVC)	(0:10)
Number of main meals (NCP)	(0:10)
Consumption of food between meals (CAEC)	(No, Sometimes, Frequent, Always)
Physical activity frequency (FAF)	(0:10)
water c per day	(0:10)
Time using technology devices (TUE)	(0:10)
Alcohol	(No, Sometimes, Frequent, Always)

obese). These models will be rigorously evaluated using a range of performance metrics including accuracy, precision, recall, and F1 score, to identify the optimal algorithm for accurate classification.

Incorporation of XAI Techniques: To ensure the interpretability of the machine learning models, Explainable Artificial Intelligence (XAI) methodologies will be integrated. Techniques such as SHAP, LIME, and decision tree visualization will be utilized to interpret the contribution of each lifestyle factor to the model's predictions. XAI provides a crucial layer of transparency, enabling a detailed understanding of the model's decisionmaking processes and highlighting the most influential predictors in determining weight levels.

Model Validation and Testing: The developed models will be subjected to rigorous validation. The models' generalizability will be assessed on an independent test dataset. Additionally, the interpretability and explanatory power of the models will be critically evaluated to ensure that the insights generated are both reliable and actionable.

This systematic methodology is designed to develop highly accurate ML models for weight classification and to ensure that these models provide interpretable insights. Such transparency is crucial for the practical application of these models in healthcare and for guiding individuals toward healthier lifestyle choices. Fig 3 shows the complete process of building our ML model.

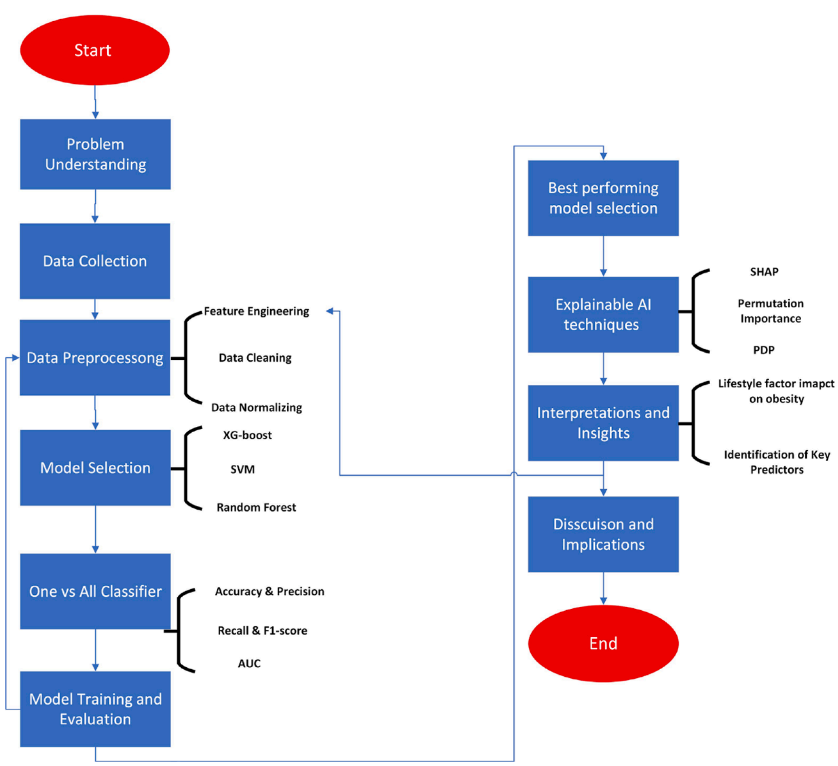

Fig. 3. The complete process of designing our ML model.

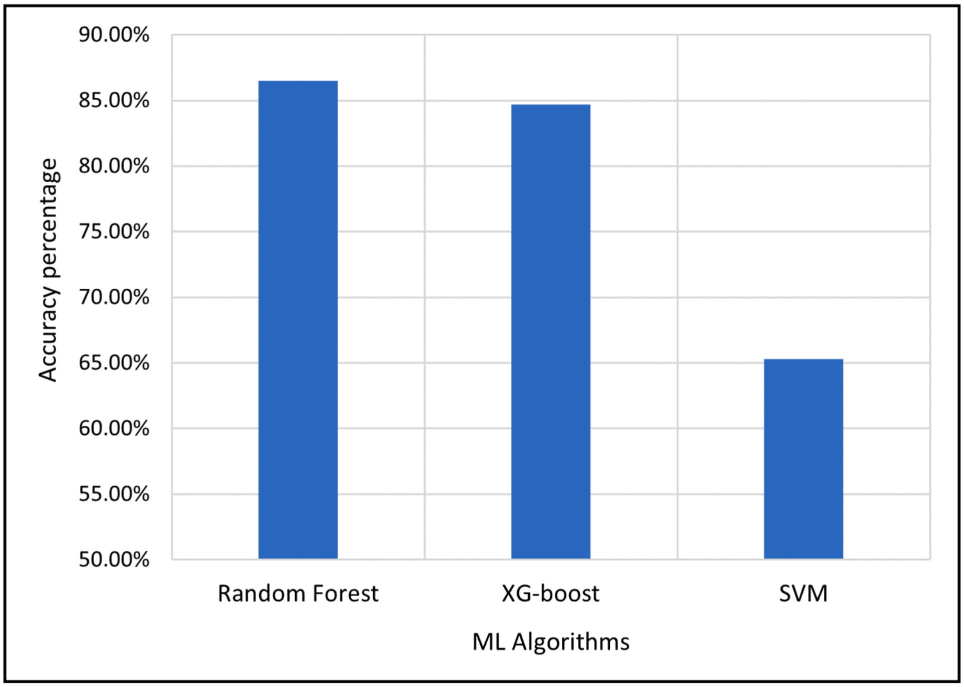

Fig. 4. The accuracy of using different ML models

4.1. *The Machine Learning algorithms*

In this paper, a comprehensive analysis of various machine learning algorithms is conducted to identify the most effective techniques for classifying obesity levels. Out of a broad range of machine learning approaches considered, three standout methods emerged as the top algorithms: XG-boost, Support Vector Machine (SVM), and Random Forest.

The decision to employ these specific machine learning techniques was a strategic one, based on their demonstrated capabilities and suitability for the task at hand. Each of these algorithms possesses unique advantages that contribute to their selection. XG-boost was highlighted for its exceptional versatility and performance. XG-boost exhibits a remarkable ability to handle missing values and adapt to data scaling requirements. This adaptability not only enhances its computational efficiency but also allows it to produce robust and commendable results, as validated by its successful track record in machinelearning competitions (Torlay et al., 2017).

Another powerful technique employed in this study is the Random Forest algorithm. Random Forest is particularly noteworthy for its ensemble nature, comprising multiple individual decision trees. The ensemble approach excels at mitigating overfitting and enhancing model stability. To make a final classification decision for a given set of inputs, Random Forest aggregates numerous classifications from these randomly constructed decision trees (Livingston, 2005). This characteristic makes it a valuable asset in handling complex datasets and yielding reliable results. By using multiple algorithms, the authors can compare the performance of each and determine which algorithm works best for their specific problem.

4.2. *One-Vs-all classifier*

Classification tasks in ML including more than two classes are called ”multiclass classification” (Grandini et al., 2020). In the used dataset, there are 4 different weight classes. Hence our problem is considered a multi-classification problem. One Versus All algorithm (OVA) learns a binary classifier for each class in a k-class classification issue to identify examples of that class from instances of the other k-1 classes (Hashemi et al., 2008). The k binary classifiers are run to categorize an instance, and the classifier with the highest confidence score is selected. In this paper, three different ML techniques which are XG-boost, Decision tree, and Random Forest were trained for each class, where the samples of that class are considered as positive examples and the samples from all other classes are considered as negative examples.

4.3. *Explainable Artificial Inelligence*

There are various types of explanations such as intrinsic or post hoc, modelagnostic or model-specific, and global or local explanations. Model-agnostic methods (Ribeiro et al., 2016) are effective methods for producing explanations without relying on fuzzy ML model internals. They have an advantageous feature that they can be applied to any ML model. In this paper, three model-agnostic methods have been used to provide explanations for the ML model outcome, including permutation importance, partial dependence plot, LIME, and SHAP

4.3.1. *Permutation importance*

The Permutation Importance (PI) approach (Gianfagna and Di Cecco, 2021) aims to address the model’s more important characteristics. Hence, after permuting the feature to assess its relevance, the increase in the model’s prediction error is calculated. A feature is considered ”essential” if shuffling its values results in an increase in model error since the feature was used by the model to make predictions, in this case, (Molnar). A feature is deemed ”unimportant” if shuffling its values causes the same or a comparable model error since the feature was disregarded for the prediction. Therefore, this strategy aims to generate a score for each feature based on how much of a difference substituting the feature with noise makes in forecasting accuracy (Hooker et al., 2021).

4.3.2. *Partial Dependence plot*

A partial Dependence plot (PDP) goes into detail on how these features affect the predictions (Gianfagna and Di Cecco, 2021). It is a plot that demonstrates the functional connection between one or more inputs and the desired outcome. The PDP shows how the most important elements might influence how the prediction evolves. If the relationship

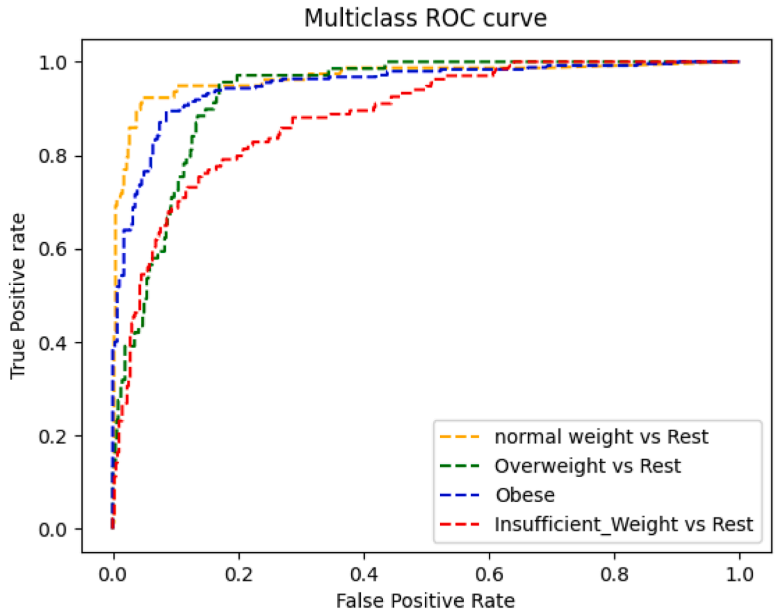

Fig. 5. The ROC curve

between the target and a feature is linear, monotonic, or more complex, it can be seen on a partial dependence plot (Molnar). PDPs offer several benefits, one of which is that it is simple to compute partial dependence charts. The PDPs can accurately depict how the feature affects the prediction on average if the feature for which the PDP was computed is not correlated with the other features. PDP has the drawback of only being valid for two inputs. In some PDP charts, the feature distribution is not visible. PDP charts only display impacts that are on average minor. Assume that, given a feature, half of your data points are in favor of the prediction (the larger the forecast, the higher the feature value), and the other half are against it. (the smaller the feature value, the larger the prediction). The PD curve can be horizontal, indicating that the feature has no impact on the forecast because the effects of both sides of the dataset could cancel one another out.

4.3.3. LIME & SHAP

Two widely used methods for model interpretability and explainability in machine learning are SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). The way LIME works is to first pick a sample to interpret. The objective is to repeatedly test the model to understand how it generates the prediction for the selected example (Thampi and Interpretable, 2022). LIME produces local explanations by locally approximating the model using a simpler model (such as a linear model) and manipulating the input data to observe how the output changes. This method can be applied to any model because it is model-agnostic. The global behavior of the model or interaction between characteristics is not taken into account by LIME, which only offers local explanations, unlike SHAP which provides global explanations. SHAP explanations are a popular feature-attribution technique for explainable AI. They quantify the impact of specific features on the forecast of a machine-learning model using ideas from game theory (Van den Broeck et al., 2022).

5. Simulation results

In this section, the ML results are shown followed by the explanations of these outcomes.

5.1. ML performance results

As mentioned before, due to the multi-classes in the dataset, the OVA

Table 3
The performance of the OVA-based Random Forest classifier

Class	Precision	Recall	F1-score	class size
Normal weight	96.2%	89.3%	0.926	252
Overweight	80.2%	93.9%	0.865	246
Obesity	85%	84.6%	0.848	228
UnderWeight	86.1%	78%	0.819	246

technique will be used. Fig. 4. shows that our best-performing model is the Random Forest by achieving 86.5% accuracy using the hold-out method. The precision score for the Overweight class is fairly low because of the small size of this class, a small number of false positives distort this score.

The performance of the classifier is measured by another evaluation metric which is the AUC equals 0.9261 as shown in Fig. 5 in which the ROC “Receiver Operating Characteristic” curve for each obesity level is depicted. ROC illustrates the association between the true positive rate and the false positive rate. Each class has its own AUC value, and the average is calculated to obtain the average AUC. In this study, the AUC values for the classification of the different 4 obesity levels ranged from 0.88 which is the under normal weight to 0.95 for normal weight. The AUC value for classifying the obese class is 0.94 which indicates that the model has a high degree of discriminatory power in classifying this level compared to the other obesity levels.

Calculating the exact time complexity of training a Random Forest model can be complex and depends on various factors, including the specific implementation details of the machine learning library being used. The time complexity of training a Random Forest can be approximately expressed as:

$$O(k\cdot(m\cdot n\log n + d\cdot n\log n))$$

where n is the number of samples in the training set while m is the number of features. k is the number of trees in the Random Forest and d represents the maximum depth of each tree.

Table 3

5.2. XAI results

To complete the cycle of machine learning, after getting the ML

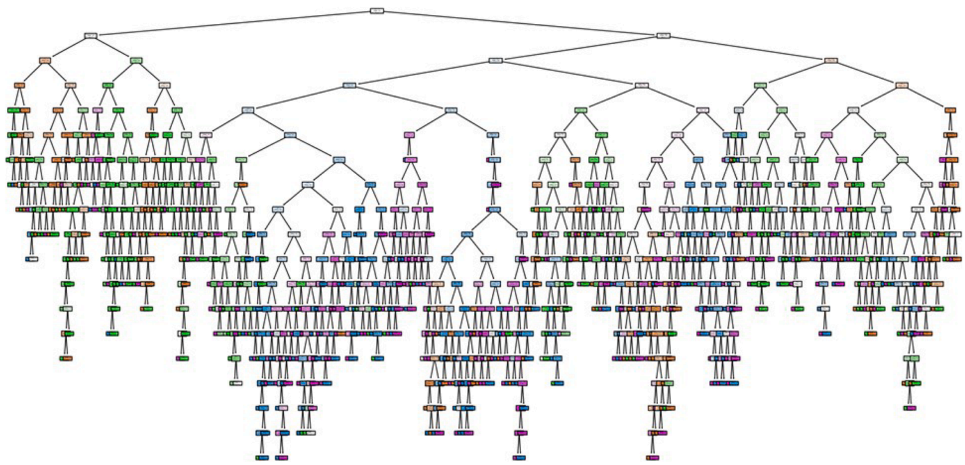

Fig. 6. Random Forest Visualization.

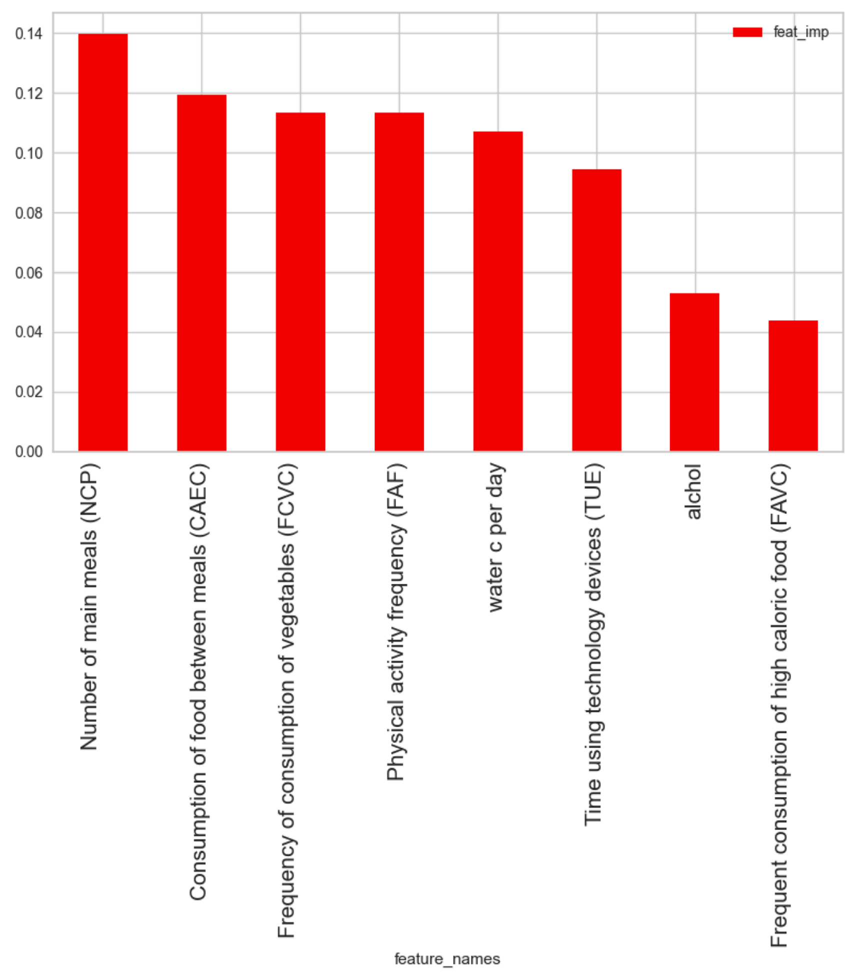

Fig. 7. permutation importance plot based on OVA algorithm

results, explaining and interpreting the results should be the final step (Khater et al., 2023). Intrinsic XAI methods can be employed to interpret the outcomes of machine learning models, including efforts to visualize the internal mechanisms of these models. In our study, we attempted to visualize the Random Forest (RF) model, as depicted in Fig. 6. This visualization illustrates the complexity inherent in the RF model, demonstrating the difficulty in comprehending the model's internal parameters and decision-making processes. The RF model, consisting of numerous decision trees, presents a challenge for direct interpretation, as the ensemble nature of the model obscures the specific contributions of individual features and decision rules. This complexity underscores the need for advanced XAI techniques to provide clearer insights into the model's internal functioning. Hence, Leveraging both model-agnostic methods and model-specific interpretability approaches, including SHAP, LIME, and Partial Dependence Plots (PDP), ensures a nuanced understanding of our RF model.

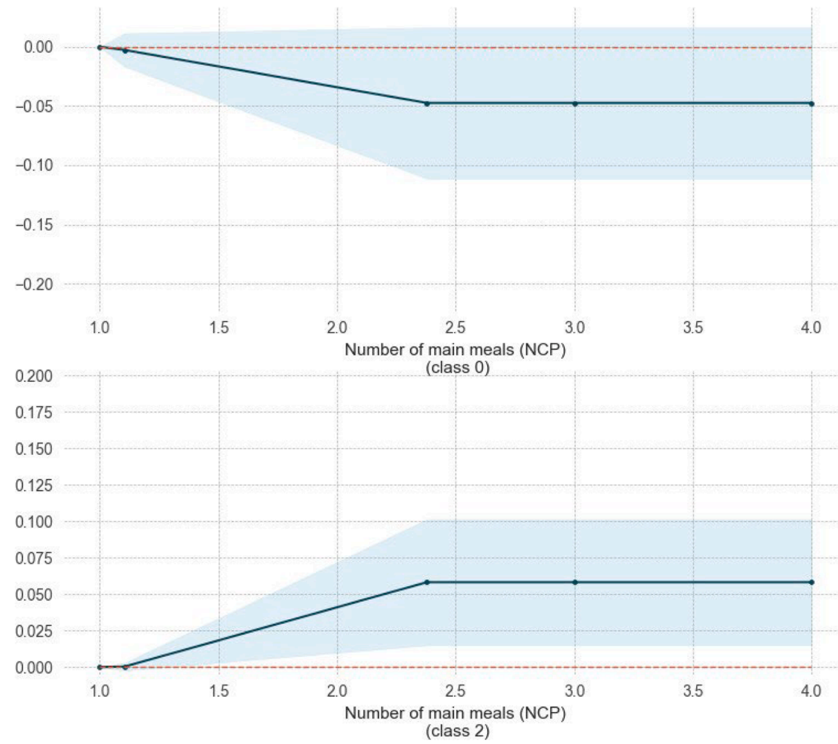

Fig. 8. Partial dependence plot

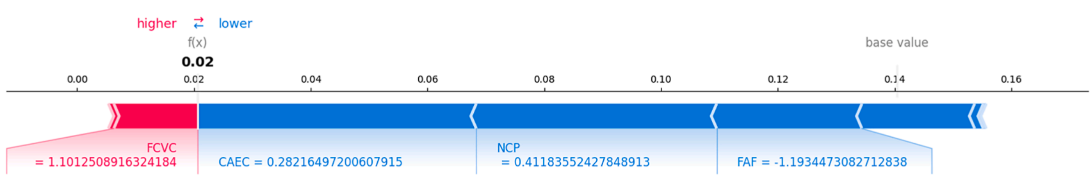

Fig. 9. Local explanation for the normal class using SHAP

5.2.1. *Permutation importance results*

PI allows the identification of the most important features. It is clear from Fig 6 that the number of main meals feature is the most important feature of the Random Forest model, followed by the consumption of food between meals.

5.2.2. *PDP results*

PDP shows the relationship between one input or more and the output target in order to see how the prediction changes by changing the most important feature. According to the permutation importance result, the PDP plot of the number of main meals feature is shown in Fig 7. The results of PDP analysis demonstrate that there is a negative relationship between the number of main meals and the predicted probability of ”normal weight”, such that an increase in the number of main meals to 2.5 meals is associated with a decrease in the predicted probability of normal weight. Conversely, there is a positive relationship between the number of main meals and the predicted probability of the ”obesity class”, such that an increase in the number of main meals is associated with an increase in the predicted probability of the obesity class.

5.2.3. *SHAP results*

SHAP can produce local explanations for the ML results. Therefore, we selected a single row from the dataset with normal weight as a target as shown in Fig 8. It is clear that when the number of main meals which has the highest length equals 1.2, the model is pushed toward predicting the normal weight class. Another instance is selected which has the obese class. As shown in Fig. 9, the time using technology has the highest positive effect on the prediction of this class especially at 0.6 hr. In Fig 8, we examined an instance representing the normal weight class. We focused on the feature ”Number of Main Meals,” which had the highest impact on pushing the model towards predicting the normal weight class. Specifically, when the number of main meals equals 1.2, the model tends to predict the individual as belonging to the normal weight class. This suggests that for this instance, having a specific number of main meals plays a significant role in classifying the individual’s weight as normal.

Fig 9 presents an instance from the obese class. We investigated the feature ”Time Using Technology,” and it emerged as the most influential factor affecting the prediction of this class, particularly at 0.6 hours. This indicates that the amount of time an individual spends using technology has a strong positive effect on the model’s prediction of obesity for this instance. In other words, individuals who spend more time using technology, especially around 0.6 hours, are more likely to be classified as obese according to the model.

These insights highlight the intricate relationships between specific features and the predictions made by the model for different weight classes. The findings emphasize the importance of certain factors in shaping the model’s decisions and provide a deeper understanding of the underlying mechanisms that contribute to predictions within each class. Such localized explanations are valuable in interpreting the model’s behavior on a per-instance basis, enabling better transparency and informed decision-making.

In addition to that, SHAP also produces global explanations for the

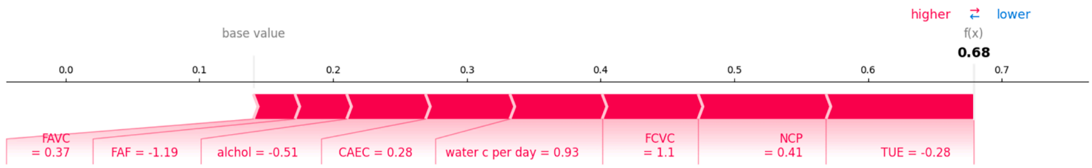

Fig. 10. Local explanation for the obesity class using SHAP

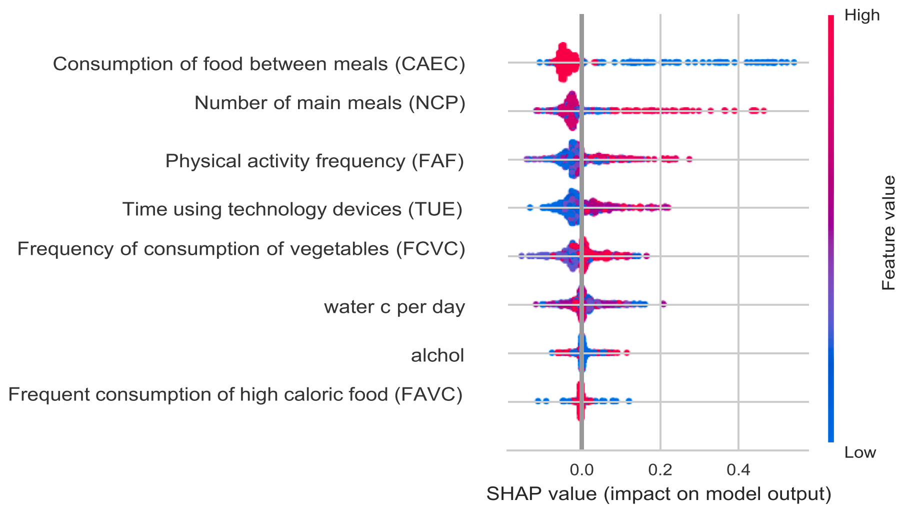

Fig. 11. SHAP summary plot for the normal weight class

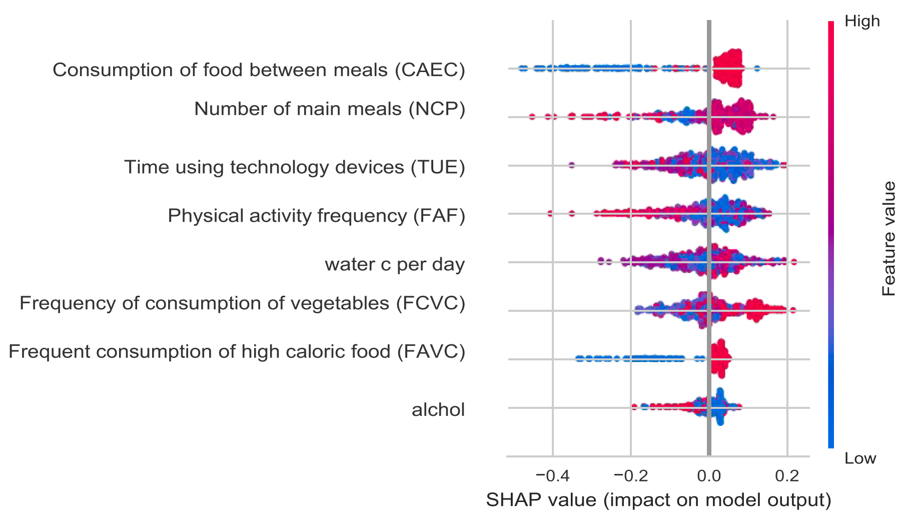

Fig. 12. SHAP summary plot for the obesity class

ML results using A tree explainer. The SHAP plot summary in Fig 10 shows that when the consumption of food between meals is low, the prediction of the ML model of the ”normal weight” class increases implying that the ”consumption of food between meals” is effecting positively on the prediction of ”normal weight” when it has a low value and vice versa for the ”obesity class” which is presented on Fig 11.

There are some features that have a neutral impact on the prediction of the normal weight class such as alcohol, frequent consumption of high-caloric food, water consumption per day, frequency consumption of vegetables, and time using technology. On the other hand, physical activity frequency has a positive effect when it is high as well as the number of main meals. Fig. 11 shows that only the number of main meals, physical activity frequency, and frequent consumption of high-caloric food have an impact on the prediction of obesity class. The results indicated that when the consumption of high-caloric food is low the prediction of the ML model to obesity decreases. In addition to that, When the person does more physical activities, the prediction of the obesity class reduces.

5.2.4. SHAP dependence plot

SHAP dependence plot is a visualization tool that aids in demonstrating how a single attribute affects an ML model's output. It is a scatter plot that displays the correlation between the relevant sample's SHAP values and the feature of interest. The x-axis of the SHAP dependence plot represents the values of the feature of interest, the y-axis represents the SHAP values, and the color of each data point represents the value of another feature that interacts with the chosen feature. The SHAP dependence plot was performed for the number of

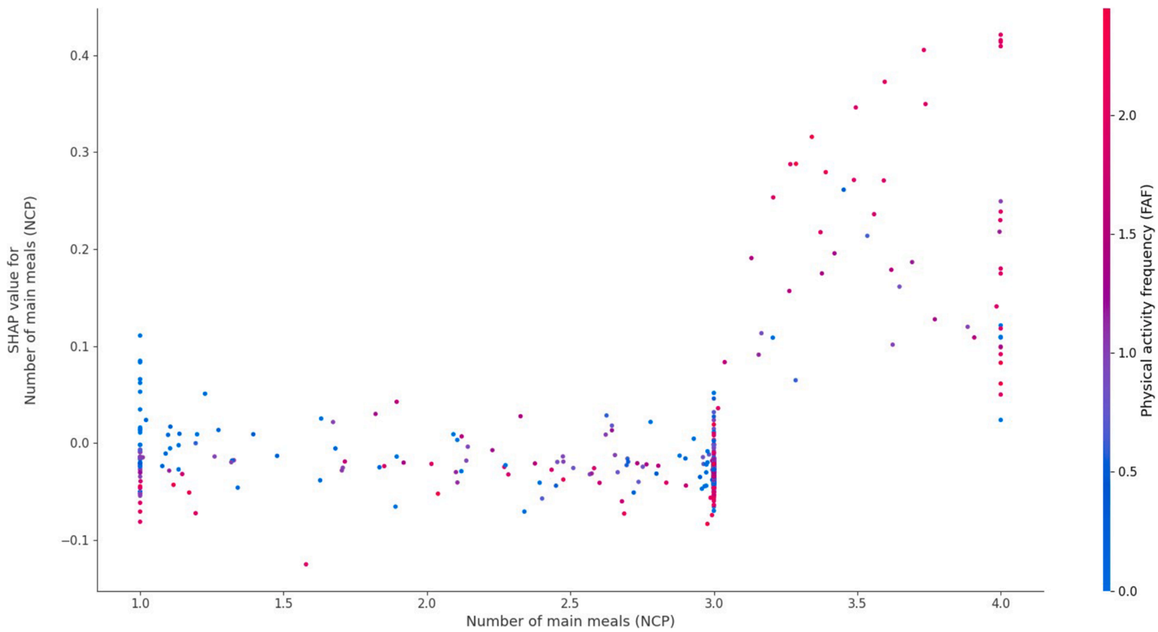

Fig. 13. SHAP dependence plot for the normal weight class

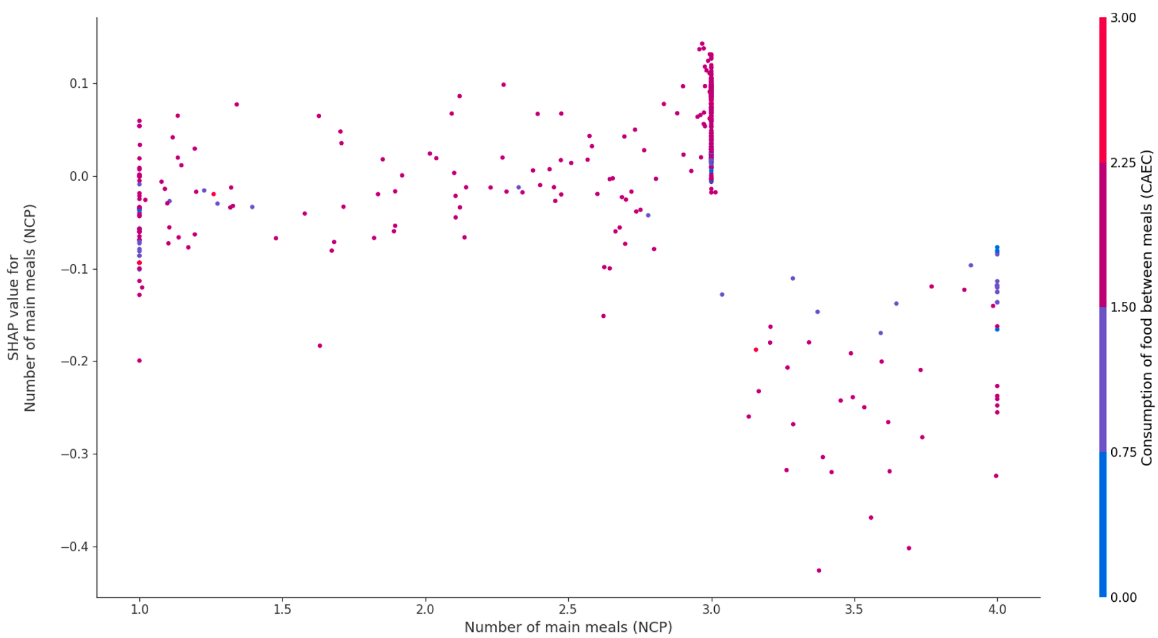

Fig. 14. SHAP dependence plot for the obesity classIn addition to the technical aspects of our project, it is crucial to consider the practical implications and potential applications of our proposed system, "Investigating the Impact of Lifestyle Factors on Obesity." The insights gleaned from this research have the potential to significantly influence various domains, including healthcare, public health, and individual well-being

main meals (NCP) feature due to its importance. Fig 12 shows the values of the NCP feature interacting with the physical activity frequency.

The plot depicts that in cases between 3 to 4 meals, the increase in physical activity increases the prediction of the normal weight class. Fig 13 represents the interaction between the consumption of food between meals (CAEC) and the NCP for the prediction of obesity class. In instances closer to 3.5 meals, the increase in CAEC will improve the prediction of the ML for the obesity class. In summary, spending around 0.6 hours more on technology had a significant positive impact on the model's ability to predict obesity in these cases. Furthermore, the model will classify the instances as obesity if the number of main meals exceeds 1.2 meals per day and if there is a rise in the consumption of food between meals. Additionally, an increase in physical activity within the range of 3 to 4 meals contributed positively to predicting the normal weight category (Fig. 14).

- Personalized Healthcare Interventions: The predictive model developed in this research can be a valuable tool for healthcare practitioners. By assessing an individual's risk of obesity based on their lifestyle factors, medical professionals can provide tailored advice and interventions, thus enabling a more personalized and effective approach to obesity management.
- Public Health Initiatives: Our system's ability to analyze lifestyle factors and predict obesity levels on a larger scale has applications in

public health. It can aid in identifying at-risk populations and informing public health campaigns and policy decisions targeting obesity prevention and control.

- Remote Monitoring and Telemedicine: With the increasing use of telemedicine and remote monitoring, our system can be integrated into these platforms to provide real-time assessments of obesity risk, allowing healthcare providers to offer guidance and support to patients from a distance.

6. Conclusion

Early detection of obesity is essential to mitigating the associated health risks. BMI, being a rapid and straightforward measure, is commonly employed as an indicator of weight status and trends. It has been aided in predicting the risk of weight gain. This approach, however, ignores several crucial elements that can provide insights into the reasons behind individuals' overweight status. As a result, this study adopted an explainable machine learning-based model for identifying obesity that uses lifestyle factors rather than BMI. Our bestperforming model achieved an overall accuracy rate of 86.5% without relying on BMI. In this paper, model-agnostic methods were utilized to provide interpretations for the ML model. For instance, the permutation importance method showed that the "number of main meals" is the most important feature in the classification of weight levels. Further explanations were revealed by PDP that the likelihood of being in the obesity class is projected to be positively correlated with the "frequency of main meals". Moreover, local and global SHAP methods were utilized to provide global and local explanations, respectively. According to SHAP, eating between meals has a positive effect on maintaining a normal weight when done in moderation. On the other hand, it has a negative impact on individuals who are classified as obese. Further work directions include the involvement of end users, clinicians, and healthcare experts in the evaluation of the proposed model and incorporation of other factors such as socioeconomic and environmental ones. Furthermore, incorporate advanced machine learning techniques such as deep learning, ensemble methods, or neural networks to further enhance the accuracy and predictive power of your model. Collecting data from more diverse populations and regions can make the model more robust.

CRediT authorship contribution statement

Tarek Khater: Writing – original draft, Conceptualization, Methodology, Software. **Hissam Tawfik:** Supervision, Conceptualization, Methodology, Resources. **Balbir Singh:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.iswa.2024.200427.

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