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Enhancing Obesity Diagnosis with Explainable AI: A Transparent and User-Friendly Approach

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Abstract

Obesity is a major global health concern that increases the risk of chronic diseases such as diabetes, cardiovascular disease, and cancer while imposing substantial socioeconomic burdens. Traditional obesity diagnosis methods often suffer from limited accuracy and poor interpretability. This study proposes an interpretable machine learning framework for obesity diagnosis using the Kaggle obesity dataset, which includes features related to Body Mass Index (BMI), dietary habits, and lifestyle factors. Several machine learning algorithms, including Random Forest (RF), Gradient Boosting (GB), Support Vector Classifier (SVC), and Extreme Gradient Boosting (XGB), were evaluated, with XGB achieving the highest accuracy of 98%. To enhance transparency and trustworthiness, the Explainable Artificial Intelligence (XAI) techniques SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) were employed. SHAP provided global explanations by identifying BMI, dietary behaviors, and physical activity as the most influential predictors, whereas LIME generated local explanations for individual predictions. Furthermore, an interactive user interface developed using Python Tkinter enables users to input lifestyle data, obtain obesity predictions, and understand the contribution of different features to the model's decision. The proposed framework combines high predictive performance with interpretability, making it a practical tool for personalized obesity assessment and management.

Keywords: Obesity, Explainable artificial intelligence, Machine learning models, User-friendly interface.

1 | Introduction

Obesity and overweight are characterized by the excessive accumulation of body fat and are associated with a wide range of adverse health outcomes. According to the World Health Organization (WHO), a substantial number of adults aged 18 years and older experience weight-related health problems, primarily due to excessive calorie intake, insufficient physical activity, and sedentary lifestyles associated with modern transportation systems [1]. Body Mass Index (BMI) is the most widely used indicator for assessing body

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weight status by relating an individual's weight to their height and classifying individuals as underweight, normal weight, overweight, or obese [2]. Lifestyle-related factors, including dietary habits, physical activity, water intake, alcohol consumption, and the consumption of fast food, have a significant impact on BMI and overall health [3]. However, obesity is a multifactorial disease, and lifestyle alone cannot fully explain its development. Genetic predisposition, together with environmental and behavioral factors, plays a crucial role in the onset and progression of obesity [4]. Obesity is a major public health concern and a significant risk factor for chronic diseases such as diabetes, cardiovascular disease, hypertension, and cancer. Evidence suggests that the increasing prevalence of obesity and the associated mortality rates have become a serious public health challenge in many countries. In addition to its adverse health effects, obesity reduces individuals' quality of life and imposes a substantial economic burden on society [5]. Despite extensive research and intervention strategies, obesity remains a major global health issue, and failing to address its underlying causes further exacerbates the problem. Therefore, addressing the escalating obesity epidemic requires innovative approaches that go beyond conventional methods.

This study proposes an interpretable machine learning framework for obesity diagnosis by integrating the Explainable Artificial Intelligence (XAI) techniques SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). These methods improve the transparency of machine learning models by providing both global and local explanations of prediction outcomes. In addition, an interactive and user-friendly interface was developed to enable users to input lifestyle-related information, obtain obesity predictions, and understand how individual factors influence the model's decisions. By combining high predictive performance with explainability, the proposed framework provides a practical and transparent decision-support tool for personalized obesity assessment and management.

2|Literature Review

Anguita-Ruiz et al. [6] developed a methodology for XAI to identify biologically relevant gene interactions in longitudinal studies in humans. The approach combines a sequence of preprocessing, knowledge extraction, and functional validation via Sequential Rule Mining (SRM) algorithms to uncover interpretable temporal patterns from gene expression data. The objective is to identify biologically meaningful interactions that could be used for experimental validation in the real world. Combining credible sources of biological data—such as GO, KEGG, and TRRUST—the given methodology delivered models capable of mining accurate, biologically valid, temporal gene interaction rules. The findings demonstrated that this strategy is capable of recognizing meaningful gene interactions related to obesity and reproducing them in different independent datasets. This approach constitutes a powerful tool for analyzing complex processes in biology to discover new targets for therapy in an interpretable fashion.

Aiosa et al. [7] introduced XAI-CDSS, a new Clinical Decision Support System integrating predictive modeling with the interpretation of XAI and graph-based visualization to approach non-communicable diseases. Through machine learning algorithms like multilayer perceptron and Extreme Gradient Boosting (XGB), this system predicts obesity-related comorbidity risk factors for diabetes, cardiovascular disease, and heart disease, with accuracy scores of 0.72 and 0.73, respectively. The XAI interface also clarifies decision-making. The graph visualization links obesity to other diseases. This linking of obesity to other diseases and related health problems helps healthcare workers have a useful tool in preventing issues, providing ongoing care, and planning treatments.

Roy et al. [8] developed OBESEYE, a dietary recommendation system that uses machine learning models—linear regression, Random Forest (RF), and LightGBM—to predict the dietary needs of individuals with obesity and non-communicable diseases. The system gives diet plans individually, considering the physical and health condition, and accurately predicts nutrient requirements. It uses XAI tools like LIME and SHAP to clarify its decision process. OBESEYE thus helps health professionals and patients to understand and comply with good dietary advice, which promotes healthier lifestyles and better management of obesity.

Khokhar et al. [9] developed SureMediks, an AI-driven digital therapeutics platform to manage obesity using a multidisciplinary approach. The technology incorporates remote monitoring, virtual coaching, AI-driven feedback, and community support to improve patient engagement and compliance. It employs short-term objectives, customized assistance, and immediate feedback to inspire users and maintain advancement. In a 24-week study including 391 people, the method attained an average weight reduction of 13.9%, exceeding the conventional 10% threshold. SureMediks integrates technology with individualized care to facilitate lasting weight reduction and promote healthy living.

Choi et al. [10] used NLP to analyze the eating habits of individuals in order to forecast metabolic diseases such as obesity and dyslipidemia by using data from the KNHANES VII survey. They identified three major dietary patterns, Traditional, Communal, and Westernized, through LDA and included them along with the sentiment scores into machine learning models such as XGB, LightGBM, and CatBoost. This improved the accuracy of disease prediction compared to conventional methods. Their findings highlight the major influence of dietary patterns on metabolic health and demonstrate the potential of artificial intelligence-based approaches for guiding tailored nutrition and public health strategies.

Bellantuono et al. [11] analyzes global lifestyle factors that have affected the popularity of dementia among 137 countries over 26 years by using XAI and complex systems methods. They used a RF model, combined with Boruta and SHAP techniques, to identify important features such as protein intake, overweight prevalence, and access to healthcare. Their results underline the strong influence of nutrition and healthcare quality on dementia rates and point to regional differences and modifiable risk factors. In this way, this approach might help bring valued insights into designing prevention strategies and promoting sustainable health policies toward dementia worldwide.

Kim et al. [12] used smartwatch data with machine learning models, including XGB, CatBoost, and Ridge Regression, to analyze factors influencing BMI in middle-aged individuals. The most important features were extracted using the BorutaSHAP algorithm; interpretability was performed using SHAP. The variables influencing BMI differed for each group of subjects with similar height. Those influencing factors, including walking speed in the morning and sleep efficiency, have proven to show the potential of wearable devices and AI in providing personalized healthcare strategies to ensure effective BMI management.

Seok and Kim [13] proposed a machine-learning-based model of sarcopenia prediction in the elderly based on features including physical activity and obesity. Several algorithms in machine learning were compared, such as Gradient Boosting (GB) Machines, XGB, and Deep Neural Networks (DNN). In this study, using the DNN algorithm, the best accuracy was 90% with obesity-related features and 84% with PA and waist circumference. The most important predictors identified by SHAP analysis were metabolic equivalent score, moderate PA, walking, BMI, and waist circumference.

Although previous studies have successfully applied SHAP and LIME to improve the interpretability of machine learning models, most have focused either on disease risk prediction or recommendation systems. Limited attention has been given to integrating highly accurate obesity prediction, comprehensive explainability, and an interactive user-friendly interface within a single framework. To address this limitation, the proposed framework combines high- performance machine learning models with SHAP- and LIME-based explanations and a practical graphical user interface, enabling users not only to obtain obesity predictions but also to understand the contribution of each feature to the model's decision-making process.

3 | Proposed Method

The overall workflow of the proposed framework is illustrated in *Fig. 1*. The figure presents the main stages of the proposed methodology, including data preprocessing, model development, performance evaluation, model interpretation, and user interface implementation. Data preprocessing and dataset description are presented in the following subsections. After preprocessing, the dataset was divided into training and testing sets, comprising 80% and 20% of the data, respectively. Several machine learning models were trained and evaluated using standard classification performance metrics. The best-performing model was subsequently interpreted using SHAP and LIME to provide global and local explanations of its predictions. Finally, an interactive and user-friendly interface was developed to predict obesity status while providing transparent and interpretable explanations of the model's decision-making process.

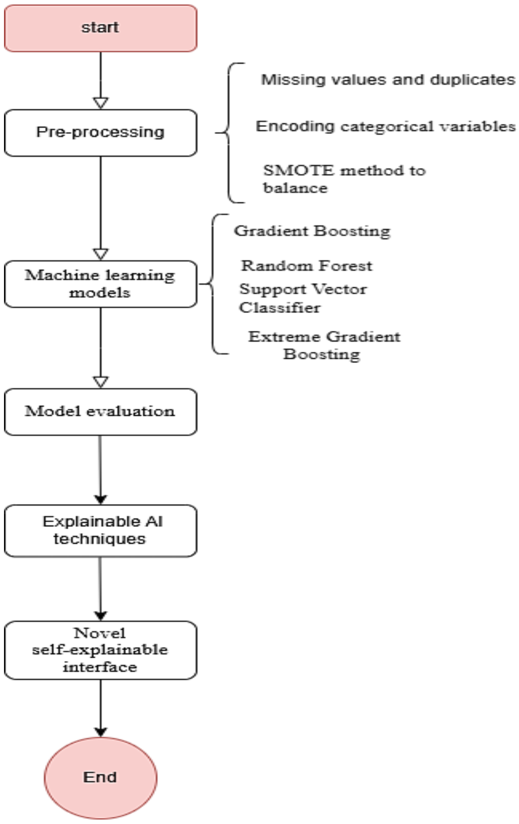


Fig. 1. Pipeline of the proposed method.

3.1 | Data Description and Pre-Processing

We used the obesity dataset sourced from Kaggle to evaluate our proposed method due to its multi-class nature and inherent class imbalance. The dataset contains 16 features and 7 classes, including age, height, weight, family history of being overweight, frequent consumption of high-calorie food (FAVC), frequency of vegetable consumption (FCVC), number of main meals (NCP), consumption of food between meals (CAEC), smoking, daily water intake (CH2O), calorie intake monitoring (SCC), frequency of physical activity (FAF), time spent using electronic devices (TUE), alcohol consumption (CALC), transportation mode (MTRANS), and the target variable, which indicates the level of obesity (Insufficient Weight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I, Obesity Type II, and Obesity Type III). The dataset contains a total of 2,111 samples.

Data preprocessing is an important step before training machine learning models. After a thorough examination of the dataset, no missing values were found. Additionally, 24 duplicate entries were identified and removed to maintain data quality. Categorical variables were encoded to make them suitable for machine learning models. Correlation analysis between the features (*Fig. 2*) revealed a strong correlation between height and weight. Therefore, these two features were combined to derive the BMI feature. As a result, the final dataset consisted of 15 input features and one target variable.

Fig. 1. Correlation heatmap.

For normalization, we used both MinMaxScaler method. The data has been scaled to the same range using the *Eq. (1)*:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}. \quad (1)$$

Applying a normalization method ensures consistent feature scaling across different variables, which improves the stability, accuracy, and robustness of machine learning algorithms. During the data exploration stage, we observed a significant imbalance in the distribution of obesity levels. Therefore, we applied the Synthetic Minority Oversampling Technique (SMOTE) to balance the dataset (*Fig. 3*). The SMOTE technique balances the dataset by generating synthetic samples for minority classes without introducing new information into the model [14].

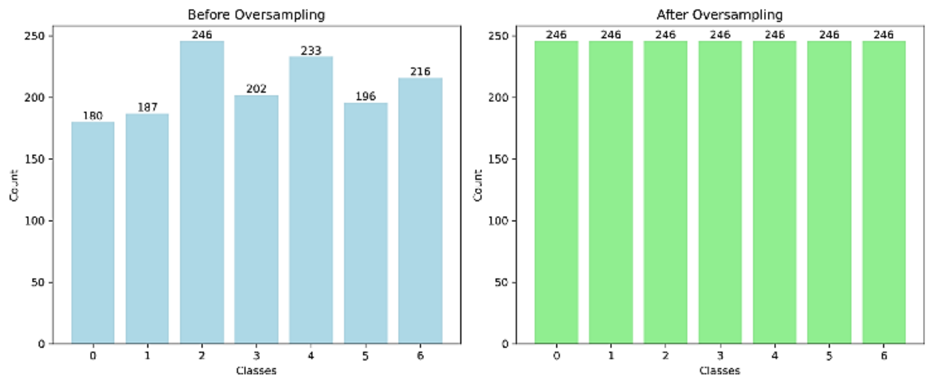


Fig. 2.Classes count of the target variable with SMOTE balancing technique.

3.2 | Machine Learning Models

In this study, four machine learning algorithms, including XGB, RF, GB, and Support Vector Classifier (SVC), were employed to classify obesity. GB is a tree-based ensemble learning method that can be applied to a wide range of loss functions. XGB extends the traditional GB algorithm by incorporating several optimization techniques that improve computational efficiency and reduce overfitting [15]. RF is a tree-based ensemble learning algorithm that constructs multiple decision trees and determines the predicted class through majority voting [16]. SVC maps input features into a higher-dimensional feature space to identify the optimal decision boundary for classification, enabling effective performance on complex datasets.

3.3 | SHAP and LIME

SHAP analyzes the contribution of each feature to a model's predictions by evaluating the effect of including or excluding individual features [16]. In this study, SHAP was used to improve the interpretability of the machine learning models and to identify the key factors influencing obesity prediction. LIME is an XAI technique that provides local explanations for individual predictions generated by machine learning models. It helps users understand how changes in input features affect the model's predictions and supports the interpretation of individual classification results.

4 | Results

4.1 | Model Evaluation

In this study, the dataset was divided into training and testing sets, with 80% of the data used for model training and the remaining 20% reserved for testing. Optuna, an open-source framework for automated hyperparameter optimization, was employed to optimize the hyperparameters of each machine learning model using 50 optimization trials. After hyperparameter tuning, the performance of four machine learning models was evaluated and compared using standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, the total optimization time for each model was measured. The evaluation results are summarized in *Table 1*, and the corresponding performance metric formulas are presented below:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}. \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}. \tag{3}$$

$$\text{F-Measure} = \frac{2\times\text{Recall}\times\text{Precision}}{\text{Recall+Precision}}. \tag{4}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}. \tag{5}$$

Table 1. Performance evaluation of machine learning models.

Models	Accuracy	F-Score	Recall	Precision	Total Optimization Time (Seconds)
XGB	0.98	0.98	0.98	0.98	107.26
SVC	0.97	0.97	0.97	0.97	20.49
GB	0.97	0.97	0.97	0.98	1105.25
RF	0.98	0.98	0.98	0.98	164.98

Accuracy is a key performance metric that represents the proportion of correctly classified instances among all observations [17]. Precision indicates the proportion of correctly predicted positive instances among all predicted positive cases, while recall measures the proportion of correctly identified positive instances among all actual positive cases. The F1-score provides a balanced evaluation of precision and recall by calculating their harmonic mean [18]. As presented in *Table 1*, the XGB model achieved the best overall performance, attaining an accuracy of 98% while outperforming the other models in terms of precision, recall, and F1-score. In contrast, SVC required the shortest optimization time, although its predictive performance was slightly lower across all evaluation metrics.

4.2 | SHAP and LIME Explanations

As shown in *Fig. 4*, the SHAP summary plot illustrates the average contribution of each feature to the predictions of the XGB model across all classes. BMI has the highest mean SHAP value, indicating that it is the most influential feature in the model. Other important features include FCVC, Gender, and Age, whereas SCC and SMOKE exhibit the lowest average contributions. In the SHAP summary plot, blue represents low feature values and red represents high feature values, while the width of each violin plot reflects the distribution of SHAP values. Overall, the results highlight the relative importance of each feature and provide insights into how individual features influence the XGB model's predictions.

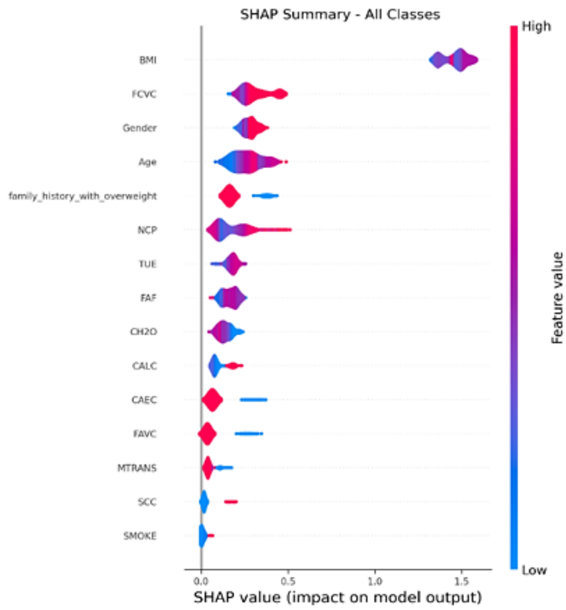


Fig. 4. SHAP summary plot showing the global feature importance of the XGB model.

As shown in *Fig. 5,* the two LIME explanation plots for the XGB model illustrate the contributions of individual features to the prediction of sample 23. The feature SMOKE ≤ 0.00 has the largest positive contribution, while BMI is the second most influential feature, further supporting the prediction of the overweight_level_II class. Other features, including CAEC, MTRANS, and NCP, also contribute positively, whereas CH2O and CALC have small negative contributions that slightly reduce the prediction score. Overall, the XGB model classifies sample 23 as the overweight_level_II class with a prediction confidence of 100%.

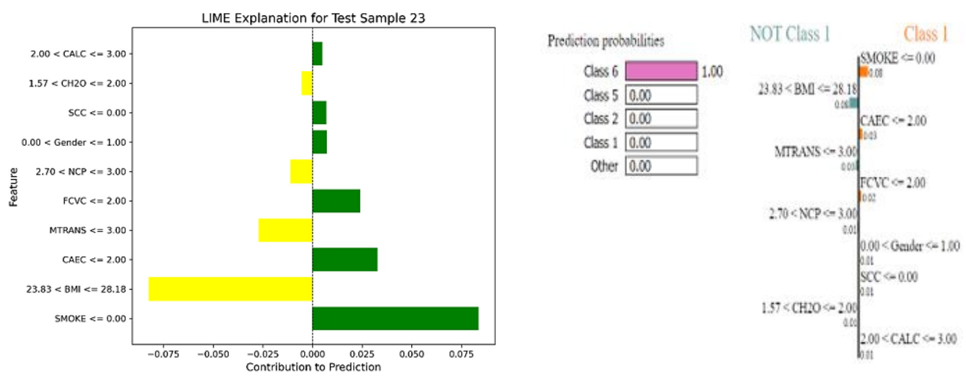
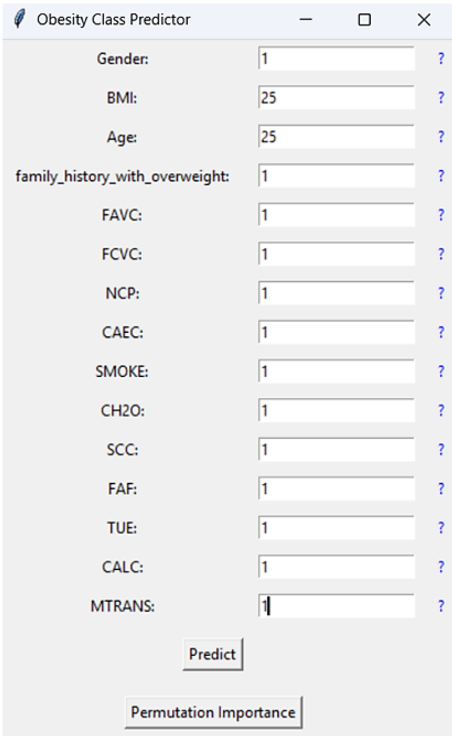


Fig. 5. LIME explanation plots for sample 23.

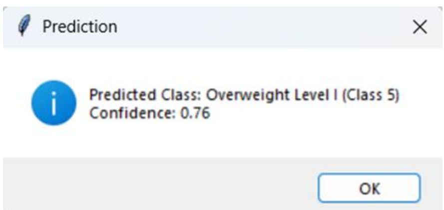
4.3 | Novel Self-Explainable Interface

We developed a user-friendly interface for obesity diagnosis based on the XGB model. The interface also employs the permutation importance method to show users the importance of each feature in the prediction process. The interface was developed using the Python Tkinter library. Users enter data such as gender, BMI, age, and lifestyle habits through a table-like layout. By hovering the mouse over the question mark beside each input field, interactive tooltips provide explanations of the expected input values. Each input is validated to ensure that the entered value is within the acceptable range. If an invalid value is entered, an error message is displayed. After the input data are validated, users can click the Predict button to display the prediction results. A message box then displays the predicted obesity class along with its confidence level.

After the prediction, users can view the importance of different features in the model's prediction. Feature importance is calculated using the permutation importance method and displayed as a bar chart to illustrate the influence of each feature. This interface provides an interactive and user-friendly tool to help users assess their obesity status and understand the contribution of each feature to the prediction. As shown in *Fig. 6*, the program processes the input data and predicts the class as Overweight Level I with a confidence of 76%. The permutation importance analysis indicates that BMI has the highest importance, followed by Age and NCP. Overall, the developed interface provides a simple and interactive user experience.



a.



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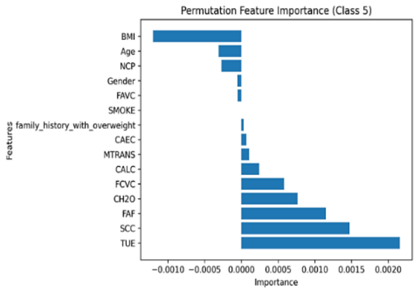

c.

Fig. 6. Proposed self-explainable obesity prediction interface; a. Obesity prediction interface, b. Predicted obesity status with confidence level, and c. permutation feature importance.

5 | Conclusion and Future Works

This study presented an explainable machine learning model for obesity diagnosis, with the XGB model achieving the highest accuracy of 98%. By integrating SHAP and LIME, the proposed model provided transparent explanations of the prediction process, highlighting the influence of key features such as BMI, dietary habits, and physical activity. In addition, a user-friendly interface was developed to improve the usability of the proposed system and support informed decision-making by both individuals and healthcare professionals. The combination of high predictive performance and model interpretability addresses an important limitation of conventional obesity diagnosis methods and supports personalized obesity management. Future work will focus on incorporating real-world data, such as wearable device data and electronic health records, to improve the model's generalizability. Furthermore, extending the feature set to include environmental and genetic factors may further enhance prediction performance. Longitudinal studies could be conducted to evaluate the model's ability to monitor obesity progression over time. Finally, deploying the proposed system as a web-based or mobile application and investigating more advanced explainability techniques could improve accessibility and provide deeper insights into feature interactions.

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