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Interpretable Multiclass Obesity Classification Using Optimized Logistic Regression Based on Anthropometric and Lifestyle Data

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Abstract. Obesity is a global public health challenge associated with increased risks of chronic diseases and significant socioeconomic burdens. Conventional obesity classification relies predominantly on body mass index (BMI), which is static and insufficient to capture the multidimensional nature of lifestyle and behavioral factors. This study aims to develop an adaptive and interpretable machine learning–based framework for multiclass obesity classification that addresses the limitations of BMI-centered approaches. An optimized Logistic Regression model is proposed and evaluated using anthropometric and lifestyle-related features, including dietary habits and physical activity patterns. The methodology involves comprehensive data preprocessing, feature encoding, stratified data splitting, hyperparameter optimization, and performance evaluation using confusion matrix analysis, learning curves, and SHAP-based interpretability. Experimental results demonstrate that the optimized Logistic Regression model achieves a high classification accuracy of 94.26% on the test dataset, accompanied by stable generalization performance, as indicated by a relatively small generalization gap between training and validation data. Learning curve analysis confirms robust learning behavior without significant overfitting, while SHAP analysis reveals that both anthropometric and lifestyle features contribute meaningfully to classification decisions. The findings indicate that Logistic Regression offers a balanced trade-off between predictive performance, generalization ability, and interpretability. This study demonstrates that an interpretable, data-driven machine learning approach can serve as a reliable alternative to conventional obesity classification frameworks and support decision-making in health-related applications.

Key words: Obesity Classification; Logistic Regression; Machine Learning; Lifestyle Factors; Interpretability

1. INTRODUCTION

Obesity is one of the global health problems that has increased significantly in recent decades and has become a major focus of attention for world health organizations [1]. This condition is not only associated with an increased risk of non-communicable diseases such as type 2 diabetes mellitus, cardiovascular disease, hypertension, and other metabolic disorders, but also has a direct impact on reduced quality of life and increased economic and social burdens in various countries [2]. The complexity of obesity as a multifactorial phenomenon influenced by diet, physical activity, genetic factors, lifestyle, and environment makes it a major challenge in effective prevention and treatment efforts [3]. Therefore, an analytical approach is needed that can accurately identify and classify obesity levels as a basis for data-driven medical and health policy decisions [4].

In the context of digital technology development and the increasing availability of health data, approaches based on Machine Learning (ML) and Data Science offer great potential for improving the accuracy of obesity status analysis and prediction [5]. Unlike conventional statistical methods, which often rely on linearity assumptions and limitations in capturing complex relationships between variables [6], Machine Learning algorithms are able to model non-linear patterns and multidimensional interactions more effectively [7]. However, the application of Machine Learning in obesity classification still faces a number of challenges, including class imbalance, data heterogeneity, complex feature correlations, and the need for models that are not only accurate but also stable and interpretable [8]. These challenges require careful model design and selection of relevant algorithms and features so that classification results can be relied upon in practical contexts [9].

Furthermore, obesity classification cannot be viewed as a binary problem, but rather as a multi-class problem that reflects various levels of physical condition, ranging from normal weight to advanced obesity [10]. This adds to the complexity of modeling because each class has

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overlapping characteristics and is not always clearly separated [11]. Obesity datasets containing attributes of eating behavior, physical activity, and demographic characteristics provide opportunities as well as challenges in extracting meaningful information [12]. Therefore, a computational approach is needed that can optimally utilize the richness of these features without sacrificing model generalization [13].

Based on this background, this study aims to develop and evaluate a Machine Learning-based obesity classification model using an obesity dataset that includes lifestyle variables, consumption habits, and individual characteristics. The main focus of this study is to examine the ability of Machine Learning algorithms to classify obesity levels accurately and consistently, as well as to identify features that have a significant contribution to the classification results. Model performance evaluation is carried out using metrics relevant to multi-class classification to ensure the reliability and validity of the results obtained

The main contribution of this study lies in presenting a comprehensive analysis of the application of Machine Learning for obesity classification with a systematic data-based approach. This study not only emphasizes the achievement of model accuracy but also the understanding of data characteristics and challenges inherent in obesity classification. The results of this study are expected to provide valuable scientific insights for researchers in the fields of Data Science and digital health, as well as serve as a reference in the development of artificial intelligence-based decision support systems for obesity detection and prevention. Thus, this study is expected to contribute to efforts to utilize Machine Learning technology more effectively to support preventive and promotive health strategies in the future.

2. RELATED WORK

Previous research on obesity in general has been dominated by clinical and epidemiological approaches that emphasize the use of anthropometric indicators, particularly body mass index (BMI), as the basis for classification and diagnosis. Ferrulli emphasizes that BMI is the primary instrument for identifying obesity, while also describing various obesity phenotypes that reflect the heterogeneity of the condition [14]. Although this study provides a comprehensive conceptual understanding of the characteristics of obesity, the discussion of classification is still descriptive and does not explore computational approaches or data-based modeling. Thus, although relevant in a medical context, this approach has not been able to capture the complexity of the non-linear relationships between lifestyle variables and behaviors that contribute to obesity.

In line with this, Bonsu emphasized obesity as a significant global health problem, with the WHO and CDC adopting a BMI threshold of ≥ 30 kg/m^2 as the standard for classifying obesity in the adult population [15]. These studies reinforce the role of BMI as the primary metric in assessing weight-related health risks. However, this single threshold-based approach has limitations in distinguishing the severity of obesity and ignores multidimensional behavioral and lifestyle factors. In addition, conventional methods tend to be static and less adaptive to individual variations, potentially resulting in less precise classifications when applied to datasets with complex characteristics.

More recent research, such as the study by Yackobovitch-Gavan, has begun to reveal inconsistencies in obesity classification between WHO and CDC standards, particularly in younger populations, with significant differences in determining weight status based on BMI z-scores [16]. These findings indicate that reliance on a single classification approach can lead to bias and inconsistency in the interpretation of obesity data. However, these studies still focus on comparing classification frameworks and have not integrated Machine Learning approaches to address these issues predictively. Therefore, there is a clear research gap in the development of Machine Learning-based obesity classification models that can simultaneously utilize various lifestyle features and individual characteristics. This study fills that gap by offering a data-driven multi-class classification approach that not only overcomes the limitations of conventional BMI but also contributes to the development of a more adaptive, accurate, and relevant obesity classification system to support artificial intelligence-based decision making.

3. METHODS

This study method is systematically designed to perform multi-class obesity classification based on machine learning, as shown in Figure 1. The main stages include data collection and pre-processing, feature exploration and transformation, data partitioning and normalization, model development and optimization, performance evaluation using various metrics, and interpretation of results through the Explainable Artificial Intelligence (XAI) approach.

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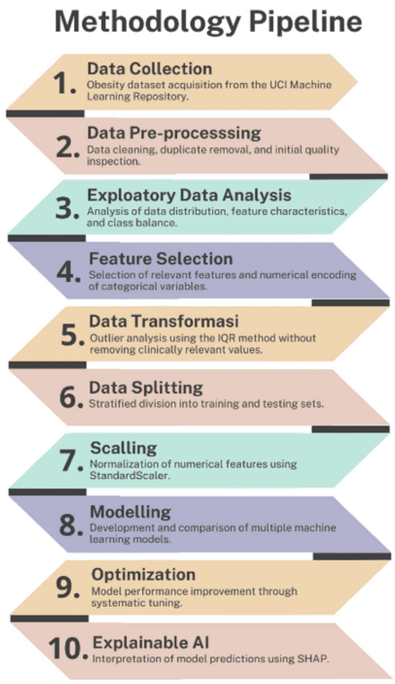

Fig. 1. Methodology Pipeline

3.1. Data Collection

Table 1 shows the features of the dataset used. This study began with data collection using a structured obesity dataset that comprehensively represents individual characteristics. The dataset includes demographic information, anthropometric attributes, and behavioral and lifestyle factors, such as age, height and weight, dietary patterns, physical activity levels, hydration habits, and daily modes of transportation. The target variable used was NObeyesdad, which classified weight status into seven categories, ranging from Insufficient Weight to Obesity Type III. This stage aimed to ensure the availability of relevant, representative, and adequate data to support the problem of multi-class obesity classification.

TABLE 1. Feature Dataset

No	Feature	Description
1	Gender	Individual's gender
2	Age	Individual's age
3	Height	Individual's height
4	Weight	Individual's weight
5	Family_history_with_overweight	Has a family member suffered or suffers from overweight?
6	FAVC	Do you eat high caloric food frequently?
7	FCVC	Do you usually eat vegetables in your meals?
8	NCP	How many main meals do you have daily?
9	CAEC	Do you eat any food between meals?
10	SMOKE	Do you smoke?
11	CH2O	
12	SCC	How much water do you drink daily?
13	FAF	Do you monitor the calories you eat daily?
14	TUE	How often do you have physical activity?
15	CALC	How much time do you use technological devices such as cell phone, videogames, television, computer and others?
16	MTRANS	How often do you drink alcohol?
17	NObeyesdad	Which transportation do you usually use?
		Obesity level

3.2. Data Pre-Processing

The pre-processing stage is carried out to improve data quality and consistency prior to the modeling process. Initial analysis includes identifying the dataset structure, attribute types, and evaluating the existence of missing values and data duplication. The results of the examination showed that there were no missing values, but a number of duplicate entries were found and subsequently deleted to avoid distortion of the data distribution and potential bias in the model training process. In addition, descriptive statistics were used to obtain an initial overview of the distribution and characteristics of numerical features.

3.3. Exploratory Data Analysis

Exploratory Data Analysis was conducted to understand the distribution patterns of the data and the relationships between variables. Analysis of the target variable distribution shows that the proportion of obesity classes is relatively balanced, which is an important condition in multi-class classification. Numerical features are analyzed through distribution visualization and correlation matrices to identify potential linear relationships, while categorical features are analyzed based on the proportion of each category. This stage provides initial insights into the relationship between lifestyle factors and obesity status.

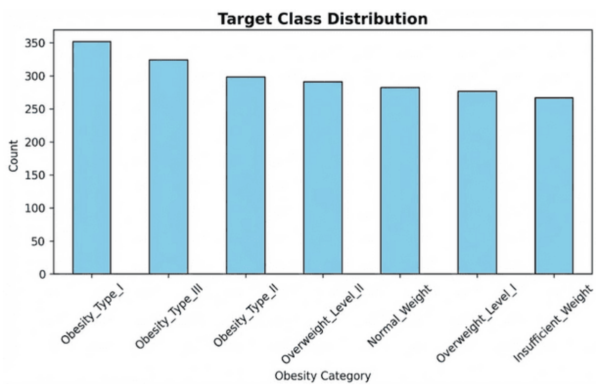

Fig. 2. Target Class Distribution

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Figure 2 shows the distribution of the NObeyesdad target class, where all obesity categories have a relatively balanced number of samples, so the dataset is considered adequate for the task of multi-class obesity classification without any indication of significant class imbalance.

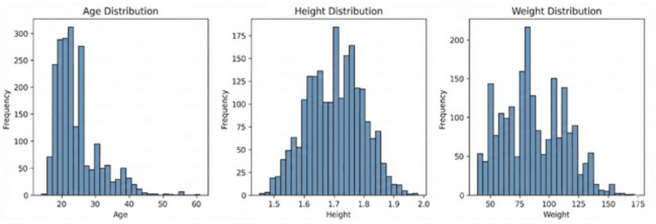

Fig. 3. Distribution of key numerical features

Figure 3 shows the distribution of key numerical features, namely age, height, and weight, which indicate a reasonable spread of data and adequately represent individual variations for obesity classification analysis.

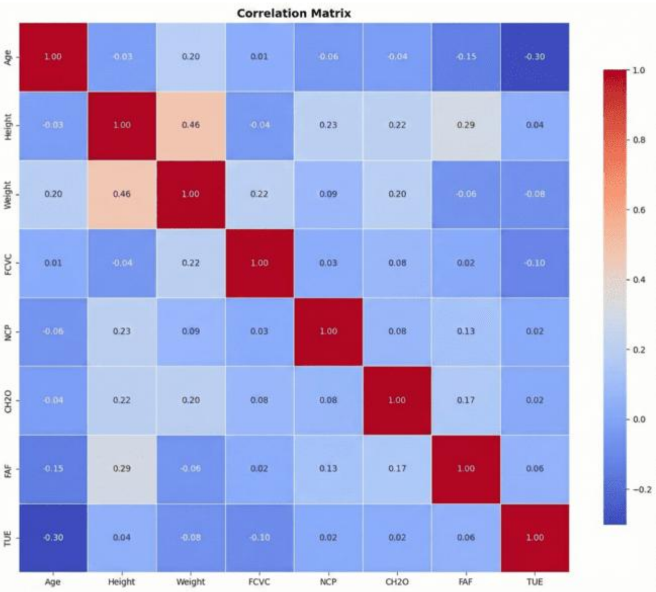

Fig. 4. Correlation Matrix

Figure 4 shows that most numerical features have low to moderate correlations, with the most notable relationship being between height and weight, indicating no strong multicollinearity and supporting the use of nonlinear machine learning models.

3.4. Feature Selection

At this stage, independent variables are separated from target variables to form a feature matrix (X) and labels (y). Feature selection is performed by retaining all clinically and statistically relevant attributes. This approach aims to ensure that important information contributing to obesity classification is not prematurely eliminated. All categorical features are converted into numerical representations using label encoding techniques to be compatible with Machine Learning algorithms. Target variables are also encoded to support multi-class classification schemes.

3.5. Data Transformation

Data transformation was performed by evaluating the presence of outliers using the Interquartile Range (IQR) method. Although a number of extreme values were identified, the data was not aggressively deleted because, in the context of obesity, extreme values can reflect real and relevant physiological conditions. Therefore, the original data distribution was retained to maintain the clinical validity and representativeness of the dataset.

3.6. Split Data

The dataset was divided into training and testing sets using a stratified split approach. This technique was applied to ensure that the proportion of each obesity class remained consistent in both subsets. Thus, model performance evaluation could be carried out more objectively and the results could be better generalized.

3.7. Scaling

Numeric feature normalization is performed using StandardScaler, so that each feature has a mean of zero and a standard deviation of one. This step is particularly important for algorithms that are sensitive to data scale, such as Support Vector Machine and K-Nearest Neighbors, and contributes to accelerating the convergence process during model training.

3.8. Modelling

The modeling stage is the core of this study, in which ten Machine Learning algorithms are applied and compared systematically, including Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, AdaBoost, Extra Trees, and XGBoost as shown in Figure 5. Each model was configured with initial parameters designed to minimize the risk of overfitting. Evaluation was performed using various performance metrics, including accuracy, precision, recall, F1-score, and cross-validation, to assess the stability and generalization ability of the model.

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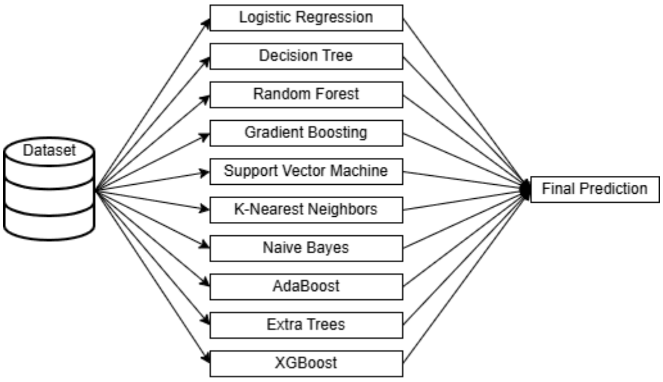

Fig. 5. Stacking Ensemble Architecture

3.9. Optimization

To improve model performance and robustness, hyperparameter optimization was performed using the Grid Search method. This process enabled systematic exploration of the best parameter combinations for each algorithm. The evaluation results showed that several models experienced increased accuracy and a decrease in overfitting gap, confirming the importance of the tuning process in the development of Machine Learning-based classification systems.

3.10. Explainable Artificial Intelligence (XAI)

In an effort to improve transparency and trust in the model, the Explainable Artificial Intelligence (XAI) approach was applied to the best model. The analysis was conducted using the SHAP (SHapley Additive exPlanations) method to identify the contribution of each feature to the model's predictions. This approach allows for a more in-depth interpretation of the dominant factors that influence obesity status classification, so that the model results are not only predictive but also scientifically explainable and relevant in the context of health decision-making.

4. RESULTS AND DISCUSSIONS

This section presents the results of obesity classification experiments. A comparative evaluation across multiple machine learning models is first reported to justify model selection, followed by an in-depth analysis of the optimized Logistic Regression model in a multi-class classification scheme. The evaluation focuses on three main aspects, namely prediction performance and classification error patterns, model generalization ability based on learning curve analysis, and model interpretability through feature contribution analysis. All results are presented to compare model performance before and after hyperparameter optimization.

4.1. Comparative Performance of Machine Learning Models

Before discussing the classification results in depth, a performance comparison was conducted against several commonly used Machine Learning algorithms, including Decision Tree, Random Forest, Gradient Boosting, and Support Vector Machine, both before and after the optimization process. Table 2 shows that some ensemble-based models were able to achieve very high training accuracy after optimization. However, this improvement was often accompanied by a relatively large overfitting gap, which indicates a decrease in generalization ability on the test data. In contrast, Logistic Regression showed consistent performance improvement between training and testing data, with a relatively small and stable accuracy gap. After optimization, this model achieves competitive testing accuracy compared to other models, accompanied by a controlled overfitting gap. These findings indicate that Logistic Regression has a better balance between predictive performance and generalization ability. Furthermore, compared to more complex models, Logistic Regression offers a higher level of interpretability and more stable learning behavior, as will be discussed further through learning curve and SHAP analysis. Based on these considerations, Logistic Regression was selected as the final model in this study, as it provides the most optimal compromise between accuracy, stability, and transparency in the context of obesity classification based on health data.

TABLE 2. Model Comparison Results

Model	Train_ Acc	Test_ Acc	Overfit_ Gap	Improvement
Logistic Regression (Before)	0.89	0.89	0.005	0.052
Logistic Regression (After)	0.95	0.94	0.016	
Decision Tree (Before)	0.82	0.81	0.006	0.105
Decision Tree (After)	0.93	0.92	0.11	
Random Forest (Before)	0.93	0.89	0.036	0
Random Forest (After)	0.93	0.89	0.034	
Gradient Boosting (Before)	0.93	0.89	0.038	0.045
Gradient Boosting (After)	0.99	0.94	0.052	
SVM (Before)	0.94	0.88	0.065	0.040
SVM (After)	0.96	0.92	0.39	
KNN (Before)	1.00	0.80	0.19	0.052
KNN (After)	1.00	0.85	0.14	
Naive Bayes (Before)	0.59	0.59	-0.0061	0
Naive Bayes (After)	0.59	0.59	0.0055	

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Model	Train_ Acc	Test_ Acc	Overfit_ Gap	Improvement
AdaBoost (Before)	0.41	0.42	-0.0094	0.0359
AdaBoost (After)	0.45	0.46	0.0076	
Extra Trees (Before)	0.85	0.82	0.0338	-0.0096
Extra Trees (After)	0.84	0.81	0.0356	
XGBoost (Before)	0.91	0.89	0.0226	0.0622
XGBoost (After)	0.98	0.95	0.0341	

4.2. Model Performance and Confusion Matrix Analysis

Figure 6 shows that the Logistic Regression model before optimization achieved a testing accuracy of 0.8900. The confusion matrix shows that most obesity classes can be classified well, especially in the Obesity Type I, Obesity Type II, and Obesity Type III categories, which show low classification error rates. However, relatively high misclassification was still found in classes with clinically similar characteristics, especially between Normal Weight, Overweight Level I, and Overweight Level II. This pattern indicates the limitations of linear models in separating classes with overlapping feature distributions.

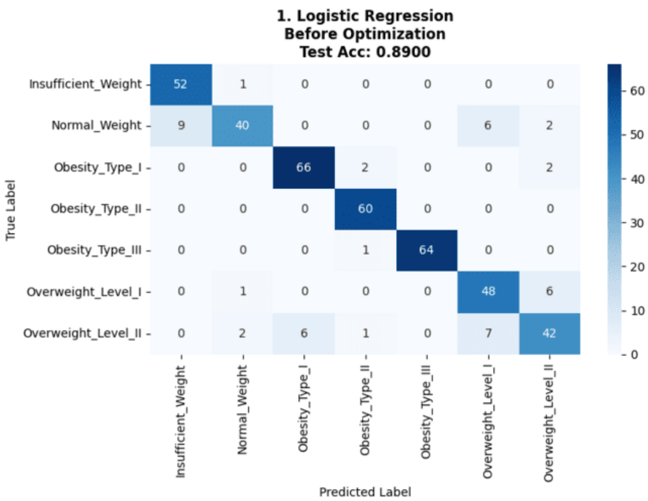

Fig. 6. Logistic Regression Before Optimization

After hyperparameter optimization, as shown in Figure 7. The model's performance improved significantly with a testing accuracy of 0.9426. The post-optimization confusion matrix showed an increase in the number of correct predictions in almost all classes, especially in the Normal Weight and Overweight Level II classes, which previously had higher error rates. The decrease in misclassification between adjacent classes indicates that the optimization successfully improved the model's discriminatory ability without causing overfitting. These results confirm that the right parameter configuration plays a crucial role in improving the performance of Logistic Regression in multi-class obesity classification problems.

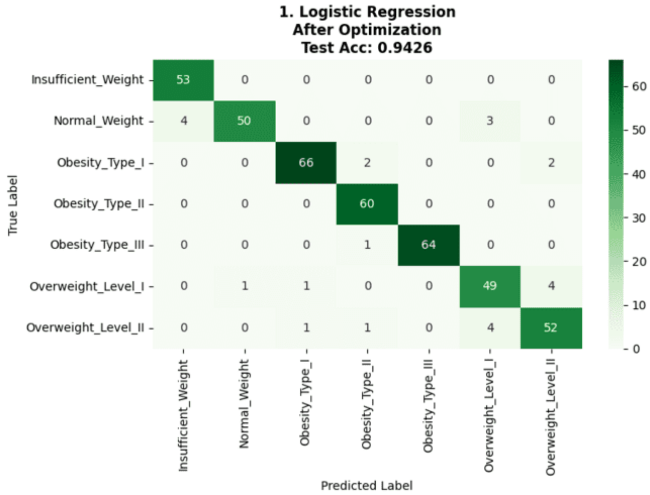

Fig. 7. Logistic Regression After Optimization

4.3. Learning Curve Analysis and Generalization Ability

Learning curve analysis was performed to evaluate the learning behavior of the model and its generalization ability to unseen data. Before optimization, as shown in Figure 8. The curve showed that the training score increased gradually and stabilized at a value close to 0.89 as the training data size increased. The cross-validation score on small data sizes was still relatively low but increased consistently as more data was added. The gap between the training and cross-validation curves was relatively small, with a generalization gap value of 0.0205, indicating that the model did not experience significant overfitting, but still had moderate bias.

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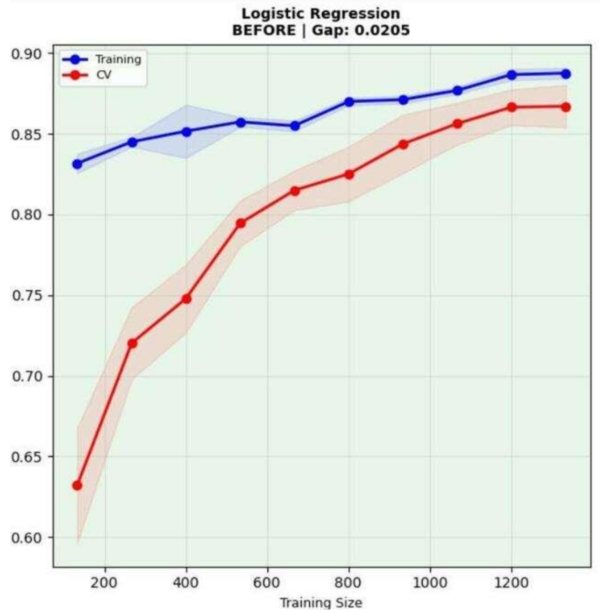

Fig. 8. Learning Curve of Logistic Regression before optimization

After optimization, Figure 9 shows a consistent improvement in both curves. The training score increases to exceed 0.95, while the cross-validation score reaches a value close to 0.94 on a larger training data size. The convergence between the two curves becomes more stable, with a generalization gap of 0.0214. The very small change in the gap (Δ = −0.0009) indicates that the improvement in model performance is not accompanied by an increase in variance, but rather comes from a more optimal parameter configuration.

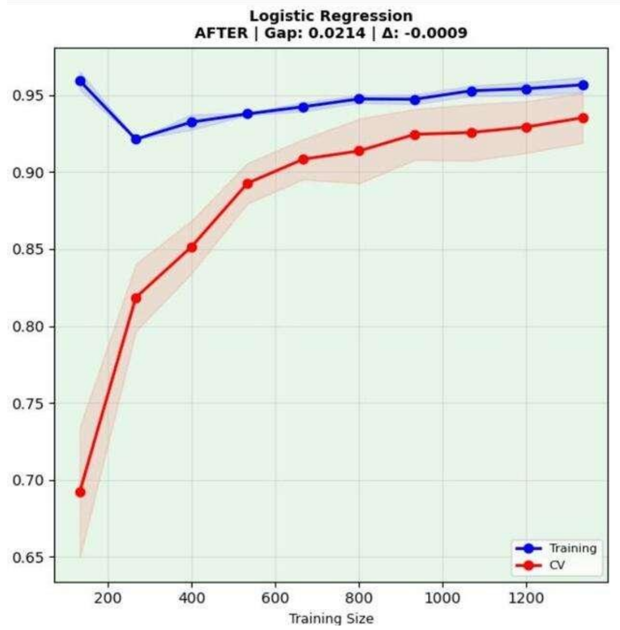

Fig. 9. Learning Curve of Logistic Regression after optimization

In addition, the reduction in fluctuations in the cross-validation curve after optimization indicates an increase in model stability against training data variation. This confirms that the optimized Logistic Regression model is able to utilize additional data more efficiently and has a better bias–variance balance. Thus, the learning curve analysis confirms that the increase in accuracy obtained is robust and generalizable.

4.4. Model Interpretability Based on SHAP Analysis

To improve transparency and confidence in the classification results, model interpretability analysis was performed using the SHAP approach. The SHAP summary in the result plot of Figure 10 show that the Weight feature has the most dominant contribution to the classification decision, followed by Height and Gender. The dominance of these anthropometric features is consistent with the conventional clinical approach that places weight and height as the main indicators in assessing obesity status.

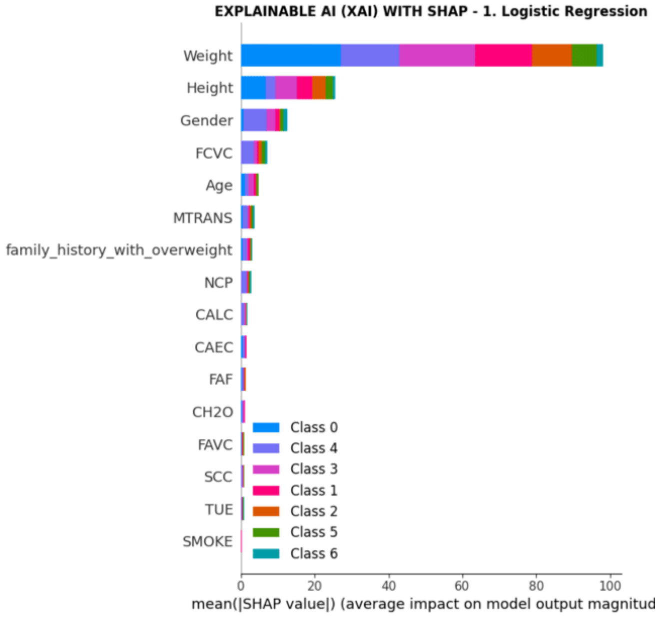

Fig. 10. Explainable AI

In addition, behavioral features such as FCVC (frequency of vegetable consumption), FAF (physical activity), and CH2O (water consumption) also contributed to the model's predictions, albeit to a lesser extent. The distribution of SHAP values shows that feature contributions vary between classes, indicating that the model does not rely on a single variable but combines various factors to distinguish different levels of obesity.
These findings show that Logistic Regression not only produces accurate predictions but also maintains a high level of interpretability. This is an important advantage in the context of health applications, where understanding the basis of the model's decision-making is a crucial aspect.

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4.5. Discussions

Previous studies on obesity classification have predominantly relied on Body Mass Index (BMI) as the primary indicator, as highlighted in works by Ferrulli, Bonsu, and others. While this approach offers simplicity and ease of implementation, it remains inherently static and insufficient to reflect the multifaceted nature of obesity, particularly with respect to behavioral and lifestyle influences. Furthermore, findings reported by Yackobovitch-Gavan reveal notable discrepancies between World Health Organization (WHO) and Centers for Disease Control and Prevention (CDC) classifications, underscoring potential inconsistencies and biases associated with single-threshold BMI-based categorization.

In contrast to these conventional methods, the present study proposes a multi-class machine learning framework that simultaneously incorporates anthropometric and lifestyle-related features. This integrated approach enables a more nuanced representation of obesity status by capturing interactions among multiple determinants. Experimental evaluations demonstrate that, following model optimization, the proposed framework achieves consistently high classification accuracy while significantly reducing misclassification among clinically adjacent categories, such as Normal Weight and Overweight, which are often problematic in traditional BMI-based schemes.

An important contribution of this study lies in the evaluation of model learning behavior and generalization performance. The learning curve analysis indicates that the optimized Logistic Regression model exhibits not only improved predictive accuracy but also stable generalization across training and validation data. The relatively small generalization gap observed before and after optimization suggests that the performance gains are robust and not driven by overfitting or dataset-specific characteristics. This aspect distinguishes the present work from earlier studies, which typically focus on final accuracy metrics without examining learning dynamics or generalization risk.

Despite employing a machine learning-based methodology, the proposed model retains interpretability through SHAP-based analysis. The prominence of weight and height as dominant features is consistent with established clinical literature, reaffirming the relevance of anthropometric indicators in obesity assessment. At the same time, the observed contributions of lifestyle factors—such as physical activity levels and dietary patterns—highlight the model's ability to capture dimensions of obesity that are frequently overlooked in traditional approaches. Consequently, this study bridges the gap between classical clinical frameworks and modern data-driven techniques, offering an interpretable and empirically grounded solution that has the potential to support more comprehensive and evidence-based decision support systems.

TABLE 3. Study Comparison

Aspect	Previous Research	This Study
Classification basis	BMI and BMI z-score (WHO, CDC) [16]	Multivariate (anthropometric + lifestyle)
Types of approaches	Clinical, epidemiological, descriptive [15]	Data-based machine learning
Class granularity	Generally binary or limited [14]	Multi-class (7 levels of obesity)
Adaptability to data	Static (fixed cut-off) [15]	Adaptive through model learning
Generalization evaluation	Not analyzed [14]	Learning curve & CV
Interpretability	Based on clinical rules [16]	SHAP (feature attribution)

Table 3 confirms that this study differs significantly from previous studies in that it applies a data-based machine learning approach and multivariate variables, thereby producing a more detailed and adaptive multi-class obesity classification.

5. CONCLUSIONS

This study aims to develop and evaluate a Machine Learning-based obesity classification approach that can overcome the limitations of conventional approaches based on body mass index (BMI), which are static, descriptive, and less adaptive to the complexity of lifestyle factors. Based on the results of experiments and analyses conducted, the study objective was effectively achieved through the application of an optimized Logistic Regression model in a multi-class obesity classification scheme.

The evaluation results showed that hyperparameter optimization significantly improved model performance, as reflected in increased classification accuracy and a decrease in the misclassification rate between obesity classes with clinically similar characteristics. Confusion matrix analysis confirms that the model is able to distinguish seven levels of weight status more consistently than a single threshold-based approach. In addition, learning curve analysis shows that this performance improvement is stable and generalizable, with a relatively small generalization gap both before and after optimization. These findings indicate that the model is not only accurate but also has a good bias-variance balance.

The main contribution of this study lies in providing an adaptive and transparent data-driven obesity

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classification framework. Unlike previous studies that focused on BMI indicators alone, this study simultaneously integrates anthropometric and lifestyle behavior features. Interpretability analysis using SHAP shows that although weight and height features remain dominant factors, lifestyle variables such as physical activity and consumption patterns also contribute to classification decisions. This reinforces the clinical relevance of the model while increasing confidence in the prediction results.

Although various Machine Learning algorithms have been evaluated in this study, including tree-based models and ensemble methods, Logistic Regression was chosen as the main model because it showed the most optimal balance between predictive performance, generalization ability, and interpretability. The evaluation results show that this model achieved competitive accuracy after hyperparameter optimization, with a relatively small and stable generalization gap based on learning curve analysis. These findings indicate that Logistic Regression is able to utilize data information efficiently without showing a tendency to overfit, a characteristic that is not always consistent in more complex models.

In addition, the main advantage of Logistic Regression lies in the level of transparency and ease of model interpretation. Integration with SHAP analysis allows for clear and consistent explanations of each feature's contribution to the classification decision, which is particularly important in the context of healthcare applications. Compared to other models that are more complex and tend to behave as black boxes, Logistic Regression provides a better balance between accuracy and clarity of decision-making. Therefore, the selection of Logistic Regression in this study is not solely based on numerical performance, but also on considerations of stability, reliability, and practical relevance to support a reliable obesity classification system oriented towards real-world application.

Overall, this study shows that a multivariate Machine Learning approach can serve as a more adaptive and consistent alternative to conventional obesity classification frameworks. By combining high predictive performance, stable generalization capabilities, and adequate interpretability, the proposed model has the potential to support the development of artificial intelligence-based decision support systems in the field of health. These findings are expected to serve as a foundation for further study exploring more complex models, more diverse datasets, and direct application in clinical contexts and data-driven health policy.

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