CAAI Transactions on Intelligence Technology

WILEY

ORIGINAL RESEARCH OPEN ACCESS

A Novel AI-Driven Expert System for Obesity Diagnosis and Personalised Treatment

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Received: 11 September 2024 | **Revised:** 22 February 2025 | **Accepted:** 22 May 2025

Handling Editor: Maoguo Gong

Funding: This research was supported by the National Research, Development and Innovation Office (NKFIH) (Grant 2024-1.2.3-HU-RIZONT-2024-00030).

Keywords: artificial intelligence | bioinformatics | intelligent systems | machine learning | recommender systems

ABSTRACT

Obesity is a major risk factor for chronic diseases, underscoring the need for early diagnosis and effective management. This study presents a novel expert system designed to accurately classify obesity levels and provide personalised treatment recommendations. Five machine learning algorithms—decision tree, random forest, multinomial logistic regression (MLR), Naive Bayes, and support vector machine (SVM)—were evaluated using the SEMMA data mining methodology and the tidymodels framework. MLR demonstrated the highest accuracy (97.48%) and was selected as the final model. The system features a user-friendly interface built with R Shiny, facilitating real-time interaction and a seamless user experience. Treatment recommendations are generated through if-then rule-based logic, ensuring tailored guidance for each obesity category. Comparative analysis highlights the system's superior diagnostic accuracy and practical application in treatment guidance. Its accessibility, particularly in underserved rural populations, enhances public health outcomes by enabling early diagnosis, targeted interventions, and proactive obesity management.

1 | Introduction

Obesity is closely linked to numerous chronic diseases and significantly impacts on broader social structures, including families, employment and the economy. Early detection and intervention are crucial in addressing this growing public health crisis. However, current methods for assessing obesity, including traditional measurements and artificial intelligence (AI) techniques, have notable limitations. These methods often fail to capture the complexity of factors contributing to obesity. They are hindered by high costs, accessibility issues and limitations in the accuracy of machine learning (ML) algorithms. Additionally, many of these methods lack the integration of diagnosis and treatment recommendations, a gap that this study aims to address. The obesity pandemic has become one of the most significant public health challenges, with its prevalence tripling over the last 40 years [1]. This increase has profound implications for physical health, as obesity is a key risk factor for chronic conditions such as cardiovascular diseases, diabetes, high blood pressure, sleep disorders and skin problems [2, 3]. Furthermore, obesity is strongly associated with mental health issues, particularly severe forms, which increase the risk of depression and anxiety disorders [4]. Obesity also significantly reduces life expectancy, with mildly obese individuals losing about 4 years and severely obese individuals losing up to 8 years of their expected lifespan [5]. Beyond health, obesity affects social structures by influencing economic outcomes, family dynamics, and employment opportunities. For instance, in labour markets, obese young women in Australia face 1.60 times the rate of discrimination compared to their nonobese peers [6] and obesity further reduces the likelihood of re-entering the job market for unemployed individuals [7]. A strong correlation exists between parents' body mass index (BMI) and their children's BMI, increasing the risk of childhood obesity [8]. Economically, obesity contributes to a significant portion of healthcare expenditure, with obese individuals incurring medical expenses approximately 30% higher than those of healthy-weight individuals [9]. The limitations of current diagnostic methods, particularly the reliance on BMI, which overlooks factors such as family history, age, and lifestyle, highlight the need for more comprehensive approaches. Expensive imaging techniques, the inconvenience for obese patients, and the lack of adequate and accurate ML models further exacerbate the problem. Moreover, existing models often do not support regular or remote obesity assessment, nor do they provide treatment recommendations. To address these challenges, this study introduces a novel expert system designed to diagnose obesity accurately and provide personalised treatment recommendations. By integrating expert knowledge, patient history, and advanced ML algorithms into a user-friendly web application, this system seeks to improve healthcare outcomes through accurate obesity classification, personalised advice, continuous monitoring, and enhanced decision-making for healthcare providers. Additionally, the system supports early intervention, empowers individuals to make informed lifestyle choices, and facilitates remote access for patients and healthcare providers. This comprehensive approach has significant potential to improve public health by enabling timely diagnosis and effective treatment of obesity.

2 | Theoretical Framework

Obesity is characterised by an excessive accumulation of body fat that poses a significant health risk. For adults, obesity is usually classified using a BMI > 30 kg/m^2 [10]. This straightforward metric, though widely accepted, has limitations, particularly in its inability to account for factors such as fat distribution and muscle mass. For children, the World Health Organisation (WHO) uses Z-scores to assess BMI development, offering a statistically precise method for categorising obesity in various age groups [11]. Figure 1 shows the BMI of 5-year-old girls and boys.

Currently, many people believe that obesity is a positive energy balance problem. However, it is a complex problem that many factors influence obesity, including internal, external, physical, psychological, and most importantly, genetic factors. The potential reasons for obesity are summarised in Table 1.

Internally, unhealthy eating habits and sedentary lifestyles are primary contributors to obesity. Urbanisation has also shifted labour patterns towards less physically demanding work exacerbating obesity rates [12]. Externally, socioeconomic status plays a crucial role. Those with lower socioeconomic status often resort to cheaper, unhealthy foods, leading to higher obesity rates, particularly among women in developed countries [13]. Technological advancements and significantly increased screen time among children have been linked to higher obesity risk [14]. Misleading advertisements for high-calorie foods further compound the issue [15]. Genetics significantly influences obesity, with studies showing that genetic factors can account for 40%–70% of obesity cases [1]. Familial obesity patterns are evident, as parental BMI strongly correlates with their children's BMI [8]. Physiological factors, including hormonal imbalances and drug side effects, also contribute to obesity, as do psychological factors such as stress-induced eating [16].

The management of obesity typically involves lifestyle modifications, pharmacotherapy, or surgical interventions. Effective treatment requires personalised approaches tailored to

TABLE 1 | Potential reasons for obesity.

Factors	Classification
Internal factors	Eating habits, insufficient exercise, lifestyle
External factors	Socioeconomic environment, misleading advertisements
Genetic factors	Obesity genetics
Physiological factors	Drug side effects, metabolism
Psychological factors	Stress

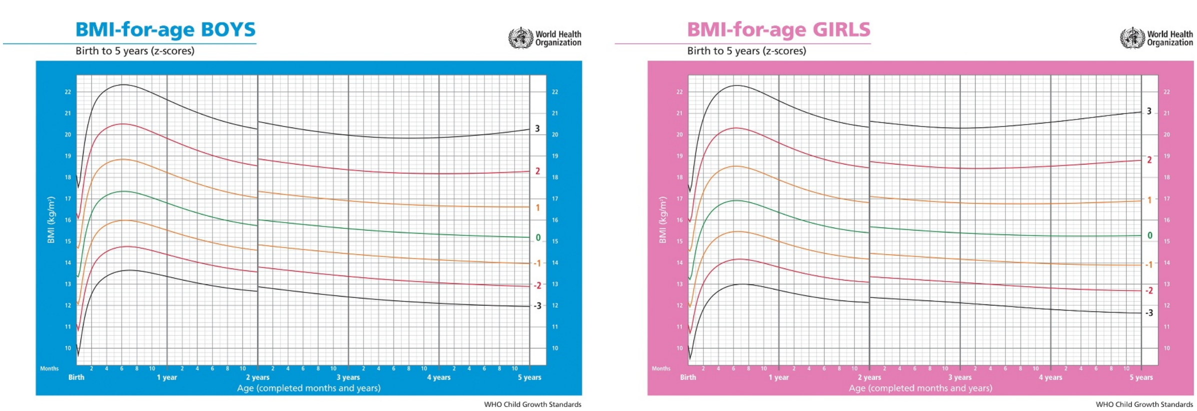

FIGURE 1 | BMI of 5-year-old: girls and boys [10].

individual needs and obesity levels [17]. Dietary strategies play a pivotal role, with high-protein diets boosting energy expenditure and low-carbohydrate diets enhancing satiety and reducing appetite [18]. Although reducing sugary drink intake is effective, low-fat diets do not significantly outperform high-fat diets in weight loss [19]. Dietary patterns such as the Mediterranean, DASH, and plant-based diets, along with strategies such as intermittent fasting, are beneficial for weight control [18]. Physical activity is equally important, with recommendations of at least 250 min of moderate-intensity weekly exercise for significant weight loss [17]. Behavioural strategies, such as self-regulation and monitoring, further enhance weight management [17]. Anti-obesity medications are a primary option for some patients whose BMI is > 30 and who are unable to lose weight effectively through dietary changes and exercise. In addition, some patients with a BMI > 40 or a BMI over 35 with serious complications, who also have difficulty losing weight through dietary changes and exercise as well as anti-obesity drugs, may be considered for weight loss surgery [15].

In obesity diagnosis, supervised machine learning techniques are instrumental due to their ability to utilise labelled data for classification tasks. Expert systems in healthcare, which integrate AI with medical knowledge, significantly advance digital transformation by aiding in diagnosis, treatment planning and reducing diagnostic errors. These systems are especially valuable in remote areas, providing virtual expertise and real-time alerts [20, 21].

3 | Literature Review

The literature review examines traditional and AI-based methods for diagnosing obesity, highlighting their strengths and weaknesses to inform the development of innovative strategies for obesity diagnosis. Traditional obesity assessment methods fall into three categories: BMI, anthropometric tools, and imaging techniques. BMI is a widely used measure that calculates body mass based on height and weight, categorising obesity into six levels according to health risk [10, 22]. However, BMI has limitations, particularly its failure to account for fat distribution, which underscores the importance of anthropometric tools. These tools, including waist circumference (WC), waist-to-hip ratio (WHR), and waist-to-height ratio (WHtR), provide insights into body fat distribution and associated health risks. For instance, WC measures abdominal fat, WHR differentiates body shapes with varying health risks [23], and WHtR is a more accurate predictor of diabetes and cardiovascular diseases [24]. Imaging techniques, such as dual-energy X-ray absorptiometry (DEXA), computed tomography (CT) and magnetic resonance imaging (MRI), offer detailed internal body data, aiding in the diagnosis of obesity-related conditions. DEXA measures tissue density using X-rays [25], CT scans provide cross-sectional images of organs and fat [26], and MRI delivers a detailed analysis of fat distribution [25]. Despite the utility of these traditional methods, they present several limitations, including the inability to consider physiological differences, population variances, and challenges in standardisation. Recognising these drawbacks, researchers have increasingly turned to AI to revolutionise obesity diagnosis. AI has become a valuable tool in disease prediction within healthcare by leveraging large datasets from hospitals and clinics to uncover patterns that improve diagnostic accuracy, reduce costs, and enhance efficiency [27]. AI also minimises human error and offers advanced predictive capabilities through ML [21]. For example, Gozukara Bag et al. [28] utilised SMOTE-NC for data imbalance and recursive feature elimination to test algorithms such as Extreme Gradient Boosting, Logistic Regression (LR), and Random Forest, with LR achieving 98.99% accuracy. Similarly, Solomon et al. [29] developed a hybrid model combining XGB, gradient boosting, and multilayer perceptron classifiers, achieving 97.16% accuracy. Other studies, such as Rodríguez et al. [30], have also demonstrated the effectiveness of ML in predicting obesity, with varying degrees of accuracy. The integration of ML algorithms into expert systems has further enhanced disease diagnosis. Albadrasawi et al. [31] created a Decision Tree-based expert system for kidney disease diagnosis, which improved diagnostic accuracy by 15% compared to traditional methods. Similarly, Aguilera-Venegas et al. [32] proposed a hybrid rule-based expert system for predicting type 2 diabetes mellitus, combining a probabilistic decision tree with expert rules, resulting in a mean squared error (MSE) of 0.388%, demonstrating superior accuracy over single-method systems. Despite the simplicity and widespread use of BMI in obesity assessment, it has notable limitations. For example, it does not account for physiological differences, such as those in athletes or the elderly, where high muscle mass or age-related fat distribution can skew results [22]. Anthropometric tools such as WC and WHR also face inconsistencies in measurement standards and are less effective for individuals with a BMI over 35 kg/m^2 [33]. Moreover, although imaging techniques such as DEXA, MRI and CT scans provide detailed body composition data, they are expensive and have limitations, such as size restrictions and increased radiation exposure [25, 34]. To address these limitations, an expert system that integrates factors such as age, gender, and genetics is proposed. Such a system aims to offer a more personalised obesity assessment and tailored treatment recommendations, effectively overcoming the shortcomings of current methods.

4 | System Architecture

This section provides an overview of the expert system's architecture and explains why R and R Shiny were chosen for its development. Figure 2 illustrates the architecture for predicting obesity risk and recommending treatments. Users input personal and lifestyle details (e.g., age, weight, transportation mode) into a web-based interface built with R Shiny. This data is processed by an inference engine, which uses ML algorithms to predict obesity risk, assigning one of six obesity levels with associated probabilities. Based on these results, if-then rules are used to generate treatment recommendations informed by expert opinions and authoritative sources. Finally, the interface displays the obesity levels and the corresponding treatment recommendations.

The choice of R and R Shiny for developing the expert system's web-based interface stems from their strengths in data analysis, ML and user experience. R's statistical analysis and data

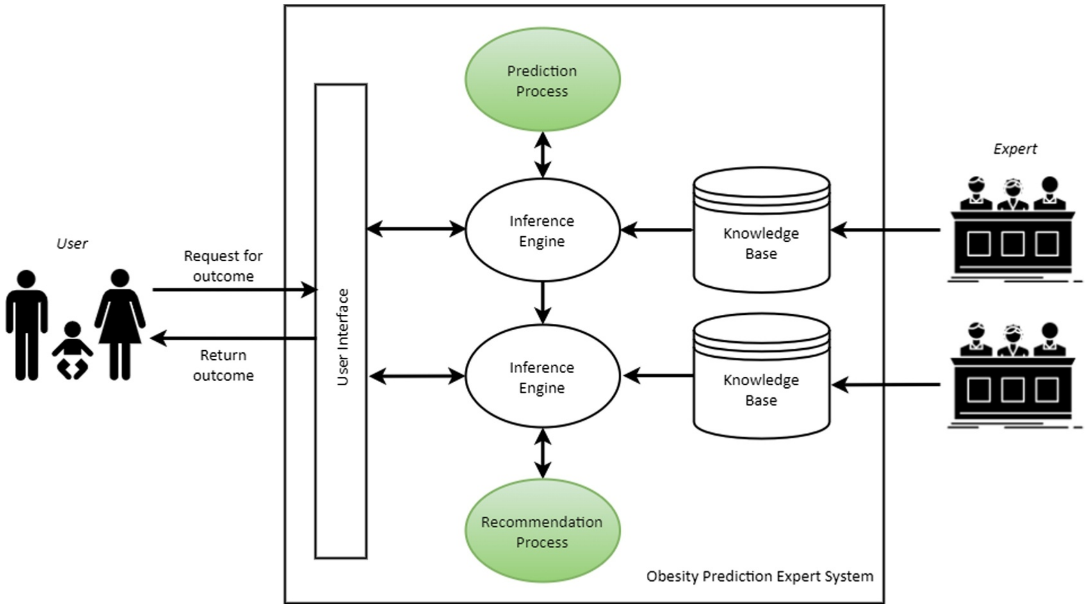

FIGURE 2 | System architecture of the expert system.

visualisation capabilities make it suitable for predicting obesity levels, and its extensive ML package ecosystem, including tidymodels, streamlines model development. Shiny, an R package, allows for seamless integration of interactive web applications with R's ML models. It improves usability by presenting complex data, such as obesity levels and treatment recommendations, in an easily accessible way through a user-friendly interface, benefiting both patients and healthcare providers. Furthermore, Shiny's real-time data processing capabilities facilitate immediate feedback, which is crucial for this expert system. Despite its higher computational costs compared to local data processing, Shiny's compatibility with future integration of external databases remains valuable.

5 | Research Methods

This section discusses the materials and methods used in the expert system. The SEMMA data mining method guided the development of the predictive model, covering sampling, exploration, modification, modelling and assessment.

5.1 | SEMMA Methodology Overview

In data mining, methodologies such as KDD (Knowledge Discovery in Databases), SEMMA (Sample, Explore, Modify, Model, and Assess), and CRISP-DM (Cross-Industry Standard Process for Data Mining) offer systematic frameworks for extracting valuable information from large datasets [35]. Although CRISP-DM emphasises aligning data mining with business objectives and KDD focuses on comprehensive knowledge discovery, both have limitations for healthcare applications, such as insufficient attention to model maintenance and interpretability.

SEMMA, on the other hand, aligns well with the goals of this study, emphasising prediction accuracy and treatment effectiveness in healthcare. The SEMMA process includes:

- *Sample*: Using the entire dataset to ensure comprehensive model training.
- *Explore*: Conducting exploratory data analysis (EDA) to understand data distribution and identify key characteristics for accurate predictions.
- *Modify*: Preprocessing the data through cleaning and normalisation to enhance model accuracy.
- *Model*: Splitting the dataset into training and testing sets and applying various ML algorithms, such as Decision Tree and Random Forest, to identify the best predictors.
- *Assess*: Evaluate model performance using metrics such as recall, accuracy, and precision, with iterative refinement as needed.

SEMMA's iterative nature supports continuous improvement, making it particularly suitable for developing a robust expert system for obesity diagnosis and treatment recommendations.

5.2 | Data Source and Description

The dataset for this research was sourced from the UCI ML Repository, a well-regarded public repository managed by the University of California, Irvine. It offers diverse datasets across fields, including healthcare, computer science, biology, and economics, making it a reliable choice for ML studies. This public dataset was collected from Colombia, Mexico and Peru and consists of 2111 records, encompassing 16 attributes related to physical condition and eating habits. The target variables have seven obesity categories. In addition, this public dataset applied the SMOTE method to balance the dataset. Given its comprehensive attributes and balanced structure, this dataset is suitable for developing an accurate obesity prediction model. For a detailed description of the dataset variables, refer to Table 2.

5.3 | Data Preprocessing

Data preprocessing is a crucial step in preparing a dataset, and it is mainly for cleaning the data and making the data format consistent for analysis or ML. The original dataset presented several issues, including unclear column names and difficulty recognising variables. Additionally, some of the data was synthetic, generated by the SMOTE method, resulting in many float values, whereas the original data consisted only of ordinal and integer values. To address these issues, several preprocessing steps were undertaken. Column names were renamed for clarity, categorical variables were encoded into numerical values, and target variables were redefined by recalculating BMI and consolidating classifications. Missing values were verified as nonexistent, and data were standardised through precision handling and rounding.

5.4 | Data Analysis

This section mainly focuses on statistical analysis and EDA, utilising a clean and consistent dataset to uncover deeper insights. The goal is to facilitate informed variable selection for future model development and optimisation.

5.4.1 | Statistical Analysis

In the first exploration phase of the SEMMA method, it is necessary to have a basic understanding of the dataset through preliminary data analysis. Statistical analysis serves as a practical approach for this purpose. Therefore, an essential exploration of the dataset was conducted using a six-number summary of descriptive statistics, a key component of statistical analysis. Only age, weight and BMI are continuous variables suitable for statistical analysis in this dataset. Other variables are {1–2}, {1–4} or {1–5} after the data preprocessing, so it is not interpretable. Therefore, statistical analysis is presented only for these four continuous variables as shown in Table 3.

- Min. stands for minimum; it is the smallest value in the dataset.
- 1st Qu. It stands for the first quartile, the median of the lower half of the dataset.
- 2nd Qu. It stands for the second quartile, also called median, which is the middle value of the dataset.
- Mean is the arithmetic average of all the values in the dataset.
- 3rd Qu. It stands for the third quartile, which is the median of the upper half of the dataset.
- Max. stands for maximum; it is the most significant value in the dataset.

TABLE 2 | Detailed description of the dataset.

Attribute	Description	Categories/range
Gender	The gender of a person	Male/female
Age	The age of a person	14–61-year-old
Height	The height of a person	1.45–1.98 m
Weight	The weight of a person	39–173 kg
Family history	Family history of obesity	Yes/no
High-calorie food	Consumption of high-calorie food	Yes/no
Vegetable consumption	Frequency of eating vegetables	Never/sometimes/always
Number of meals	Number of main meals per day	1–2/3/ > 3
Eating between meals	Frequency of eating between meals	No/sometimes/frequently/always
Smoking	Smoking habit	Yes/no
Water intake	Daily water consumption	< 1/1–2/ > 2 L
Calorie monitoring	Monitoring daily calorie intake	Yes/no
Physical activity	Frequency of physical activity	None/1–2 days/3–4 days/4–5 days
Device usage	Time spent on electronic devices	0–2/3–5/ > 5 h
Alcohol consumption	Frequency of alcohol consumption	No/sometimes/frequently/always
Transportation	Mode of transportation used	Bike/motorbike/automobile/walking/public transport
Obesity level	Obesity levels based on BMI	Underweight/normal weight/overweight I, II/obesity I–III

5.4.2 | Exploratory Data Analysis

EDA is a crucial step in model construction, aimed at gaining insights into the data through visualisation and statistical methods to identify patterns, trends, outliers and other relevant information. This part presents a detailed exploration of each variable, providing essential insights for variable selection and understanding the potential influence of these variables on obesity classification.

Figure 3 presents a bar chart illustrating the distribution of obesity levels. Each bar represents the number of individuals in each category. The overweight category has the highest count due to the merging of 'Overweight I' and 'Overweight II' during the data preprocessing phase. This approach aligns with the WHO obesity classification standards adopted in this study, which recommend categorising obesity into six levels based on BMI.

Figure 4 displays the analysis of the gender variable, indicating an approximately equal distribution of females and males in the dataset. In the underweight category, the proportion of females is higher than that of males. Conversely, in the overweight category, males significantly outnumber females. For Obesity Level III, there is a markedly higher proportion of females compared to males. The remaining categories exhibit only minor differences in gender proportions.

Figure 5 illustrates the distribution of box plots for different weight categories. The standard weight and underweight groups show a more concentrated distribution, primarily among individuals in their 20s. In contrast, the obese group has a more dispersed distribution, spanning ages 20–30, suggesting a higher likelihood of obesity within this age range. Among the obesity categories, Obesity Level I and Overweight display the largest age span, ranging from approximately 16–42 years.

The scatterplot in Figure 6 depicts the relationship between height, weight and obesity levels. The black line indicates a positive correlation between height and weight, suggesting that an increase in height is associated with an increase in weight. Thus, it can be inferred that taller individuals will weigh more.

In addition, most respondents affirmed having family members with obesity, a family history of obesity, and consuming high-calorie food, indicating that individuals classified as overweight or obese (levels I–III) often have familial obesity and a preference for high-caloric diets. Conversely, most respondents denied smoking or monitoring their daily calorie intake, suggesting that nonsmokers who do not track calories are more prone to obesity. Regarding vegetable consumption, most answered 'sometimes', though those in the Obesity III category predominantly responded 'always'. Regarding daily water intake, most individuals reported drinking 1–2 L, while fewer—especially those in Obesity II and III—reported drinking more than 2 L. Concerning electronic device usage, most respondents used them for 0–2 h per day, with fewer individuals in Obesity III spending 3–5 or more hours on devices. Most participants preferred public transportation over biking, motorbiking or walking, with individuals in Obesity III showing a notable preference for public transit. This preference and other everyday lifestyle habits correlate with higher obesity rates. For instance,

TABLE 3 | Three variables of statistical analysis.

Variables	Min.	1st Qu.	2nd Qu.	Mean	3rd Qu.	Max.
Age	14.00	19.00	22.00	23.97	26.00	61.00
Height	1.450	1.630	1.700	1.702	1.770	1.980
Weight	39.00	65.00	83.00	86.23	107.00	173.00
BMI	12.80	24.30	28.70	29.58	35.80	50.80

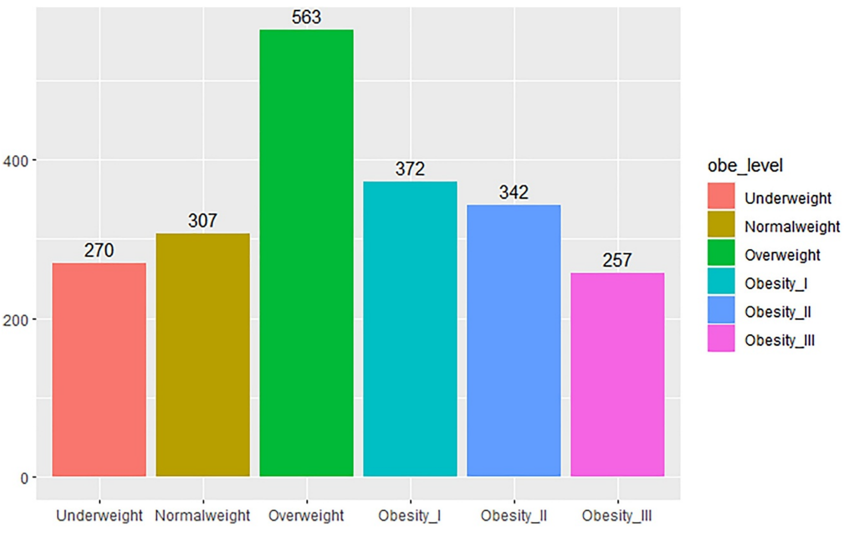

FIGURE 3 | Classification of target variables.

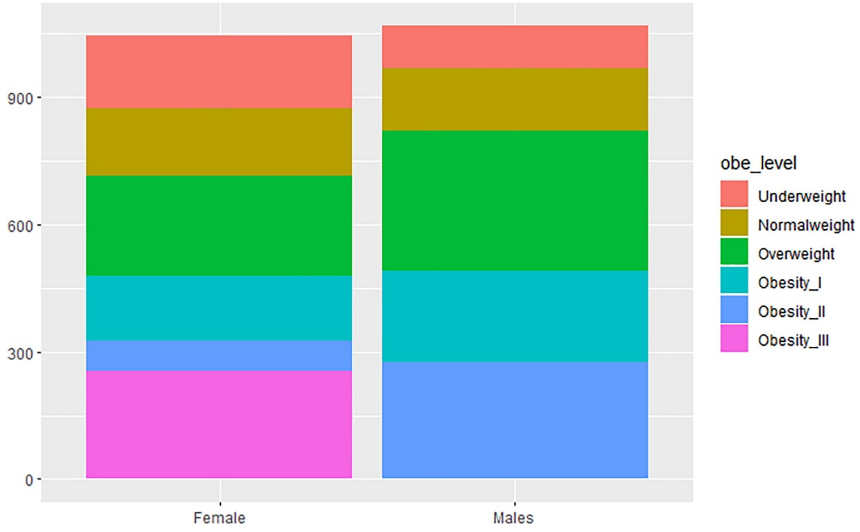

FIGURE 4 | Results of gender data distribution.

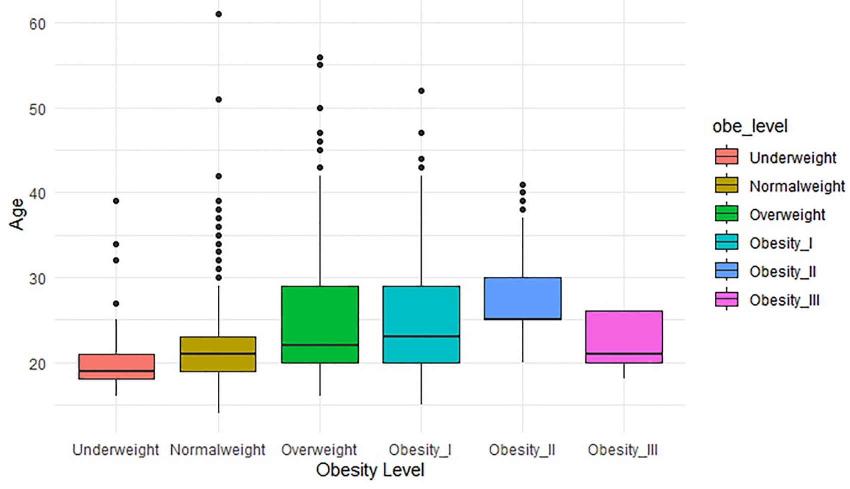

FIGURE 5 | Age distribution across obesity levels.

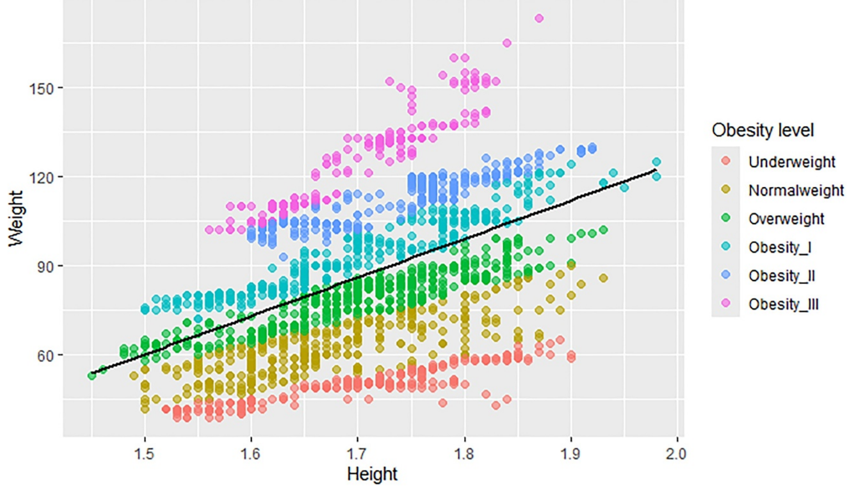

FIGURE 6 | Relationship between height, weight and obesity levels.

most respondents reported having more than three main meals per day, indicating frequent snacking and those who 'sometimes' ate between meals also had higher obesity prevalence. Most individuals did not engage in regular physical activity or exercised only 1–2 days per week, with these groups showing higher obesity levels than more physically active individuals. In terms of alcohol consumption, 'sometimes' was the most frequent response, with fewer respondents drinking frequently or always.

5.5 | Construction of Predictive Models

After ensuring the data was clean and consistent, the next step was to develop an obesity predictive model using the tidymodels framework. Tidymodels simplifies the modelling process through a structured workflow, allowing for iterative experimentation with different model architectures and parameters. The process includes:

- *Model specification:* Define the model type and parameters. For classifying obesity levels, supervised classification algorithms were chosen, including multinomial logistic regression (MLR), random forest, decision tree, support vector machine (SVM), and Naive Bayes. Among these, MLR demonstrated the highest accuracy and was selected as the final predictive model. MLR is particularly valuable for interpreting feature relationships, as it estimates the probability of belonging to a given obesity category relative to a reference category. The coefficients in MLR represent log-odds changes, which can be exponentiated to obtain odds ratios. This allows for meaningful interpretation, where positive coefficients indicate increased likelihood and negative coefficients indicate decreased likelihood of obesity classification. For example, a positive coefficient for high-calorie food consumption in the Obesity III category suggests a higher probability of severe obesity relative to the baseline category. The magnitude and direction of these coefficients help healthcare professionals identify key obesity risk factors and make personalised treatment recommendations.
- *Create recipes:* Preprocess data before training to ensure relevant variables are appropriately processed. Two recipes were created:
  - All features recipe: Includes a full set of variables (e.g., age, weight, family history, physical activity).
  - Smaller features recipe: Excludes less relevant variables to test whether a simplified model improves performance.
- *Combine models and recipes:* Multiple workflows were formed by combining models and recipes. Each workflow was evaluated using 10-fold cross-validation. The best-performing workflow was selected based on accuracy and ROC AUC (receiver operating characteristic—area under the curve). Although accuracy measures the correct classification of obesity levels, ROC AUC assesses the model's ability to differentiate between categories—critical for multi-class classification.
- *Train the model:* The selected workflow (MLR with the smaller features recipe) was used to train the final model.
- *Evaluate model performance:* A detailed evaluation is provided in the 'Evaluation of Expert System' section.

Table 4 summarises the methodology used for developing the expert system.

5.6 | Development of the Expert System

The expert system development addresses the last two research objectives with methods and tools summarised in Table 4. One of the aims is to integrate the best-trained model with R Shiny to create an expert system. The integration process ensures seamless data flow between the model and the interface, allowing for efficient processing of user input and timely delivery of predictions. R Shiny, a robust framework developed by RStudio for building web-based applications in R, consists of a user interface (UI) and server. The UI defines the web page's appearance and user interaction by specifying the layout, structure, and visual elements. The expert system's UI is organised using Shiny Dashboard components, which include a header, sidebar, and main content area. The UI is enhanced with visual elements including images emphasising key information and value boxes to present predicted results intuitively. Shiny Dashboard contributes to a well-organised visual experience, and its responsive design ensures adaptation to various devices, including smartphones and tablets, making the system accessible even for users with limited bandwidth. Integrating a user-centric design with health-focused features, the expert system aims to support individuals in rural communities by providing accessible, personalised health guidance. The server-side functionality of the Shiny application involves data

TABLE 4 | Methodology for development of expert system.

No	Research objectives	Data collection	Methods and techniques	Tools
1	Build an ML model	UC Irvine ML repository	Decision tree, multinomial logistic regression, random forest, SVM, Naive Bayes SEMMA method	R language R Shiny RStudio version 2023.09.0
2	Create expert system and web app	Output from the first phase	Shiny UI and server, HTML, CSS	
3	Provide treatment recommendations	Expert opinions, authoritative studies	Shiny UI and server, if-then rules, HTML, CSS	

management, predictive modelling and dynamic responses to user inputs. The server uses a pre-trained ML model to estimate the user's obesity level, activated through an event-driven mechanism when the user clicks the prediction button. Initially, the server collects user input and structures it into an appropriate data frame format, which the model then uses to predict obesity classification and its associated probability. Based on the prediction, the server uses if-then rules to generate personalised recommendations [36–38], including dietary, physical activity, and lifestyle guidance, thereby fulfilling the final objectives of the research. These recommendations are presented intuitively, using text and illustrative images tailored to each obesity classification. This interactive approach ensures users receive detailed, personalised guidance aligned with their health profile.

5.7 | Evaluations of Expert System

This study developed the expert system by integrating an ML model with R Shiny. The ML model and the expert system were rigorously evaluated to ensure the integration's reliability and accuracy. Standard performance metrics for the ML model include the confusion matrix, which calculates various metrics based on predicted versus actual categories; accuracy, which measures the proportion of correctly predicted instances; precision, reflecting the accuracy of optimistic predictions; recall, indicating the model's ability to identify positive cases; and the *F*1-Score, which combines precision and recall into a single measure. The receiver operating characteristic (ROC) curve also evaluates the model's ability to discriminate between obesity levels in a multiclass classification context. After considering the model, the expert system was assessed using key metrics, including sensitivity and accuracy, both crucial for diagnostic expert systems. Additionally, user satisfaction was measured through surveys, interviews, and usability tests. This comprehensive evaluation ensures that the system is user-friendly, accurate, and reliable, meets user expectations, and identifies potential areas for improvement.

6 | Research Results and Analysis

This part presents the key experimental results during the model development and details the outcomes of integrating the model into the expert system. Additionally, the evaluation results of the model and expert system are given.

6.1 | Build Prediction Machine Learning Model

The prediction model will use five ML algorithms and two recipes to train the model and predict six categories of obesity levels. Therefore, 10 workflows will be trained. These workflows were trained on 70% of the dataset and the remaining will be used for testing.

6.1.1 | Model Specification

The initial step in constructing the predictive model involved selecting appropriate ML algorithms, considering that the study aims to diagnose obesity levels, representing a multiclass classification problem. Therefore, decision tree, random forest, multinomial logistic regression, Naive Bayes and SVM were chosen for their effectiveness in handling multiclass classification tasks. The model specification process is shown in Figure 7.

Each algorithm brings distinct strengths to the model:

- Decision Tree offers interpretability, making it easier to understand the factors leading to obesity, which aligns with the study's goal of developing a user-friendly application.
- Random Forest is robust against overfitting and can handle diverse healthcare datasets with high predictive accuracy, which is essential for reliable obesity diagnosis.
- Multinomial logistic regression extends traditional logistic regression to handle multiclass classification issues, enabling the prediction of an instance's probability of belonging to each obesity level, thereby enhancing the interpretability of the expert system.
- Naive Bayes is efficient for multiclass classification, especially with unrelated features, making it a simple yet practical choice for integrating into expert systems.
- SVM excels in handling complex decision boundaries, improving the model's ability to differentiate between obesity levels accurately.

```
decision_tree_rpart_spec <-
  decision_tree(min_n = 5) %>%
  set_engine('rpart') %>%
  set_mode('classification')

rand_forest_randomForest_spec <-
  rand_forest() %>%
  set_engine('randomForest') %>%
  set_mode('classification')

multinom_reg_nnet_spec <-
  multinom_reg() %>%
  set_engine('nnet') %>%
  set_mode('classification')


naive_Bayes_naivebayes_spec <-
  naive_Bayes() %>%
  set_engine('naivebayes') %>%
  set_mode('classification')

svm_linear_kernlab_spec <-
  svm_linear() %>%
  set_engine('kernlab') %>%
  set_mode('classification')
```

FIGURE 7 | Model specification.

These algorithms were implemented using the tidymodels framework in R, ensuring a structured and consistent approach to model training and evaluation. The choice of these models aligns with the research objective of developing an accurate and reliable system for diagnosing obesity levels.

6.1.2 | Create Recipes

In the model construction process, recipes in the tidymodels framework play a crucial role in transforming input data before training a model. This aligns with the exploration phase, which focuses on selecting the most significant variables contributing to model performance. Two distinct recipes were developed for this research:

- All features (Recipe 1): This recipe includes a comprehensive set of variables such as gender, age, height, weight, family history of obesity, consumption of high-calorie food, and various lifestyle factors such as smoking, physical activity, and transportation mode.
- Smaller set (Recipe 2): This recipe focuses on a streamlined subset of variables, omitting factors such as the frequency of vegetable consumption, water intake, screen time, and alcohol consumption.

The primary purpose of creating these two recipes was to evaluate which variables would enhance the model's predictive accuracy. Recipe 1 provides a comprehensive exploration of the dataset, ensuring that no potentially relevant information is overlooked, while Recipe 2 aims to simplify the model by excluding variables with limited impact on prediction performance. This approach allows for a balanced comparison, where the complete set serves as a baseline, and the reduced set tests whether a simpler model might achieve equal or better accuracy. The results of this comparison revealed that simplifying the model by using Recipe 2 did not compromise accuracy and, in some cases, even improved it, highlighting the efficiency of a more focused feature selection approach.

6.1.3 | Combine the Model and Recipes

After figuring out the five models and two recipes, the next step is combining them. Exploring different models and variable sets helps find the most effective combination for this paper's dataset and research aims. By experimenting with various combinations of the models and recipes, it is possible to systematically evaluate the performance of multiple modelling approaches and variables to decide which combination yields the best predictive accuracy and robust results. Therefore, 10 workflows were constructed, as shown in Table 5, each representing a unique combination of models and recipes.

Before selecting the optimal workflow, several assumptions and considerations are important. Firstly, the diversity of models and recipes is crucial. This study includes decision tree, random forest, multinomial logistic regression, Naïve Bayes and SVM, along with two recipes: a full set of variables and a smaller set.

TABLE 5 | Workflows combined five models and two recipes.

No.	Workflows
1	all feasures_dtree
2	all_features_multilogit
3	all_features_rforest
4	all_features_naiveBayes
5	all_features_svm
6	smaller_set_dtree
7	smaller_set_multilogit
8	smaller_set_rforest
9	smaller_set_naiveBayes
10	smaller_set_svm

While other ML algorithms could have been used, these five were chosen due to their proven effectiveness in classification tasks. Similarly, two recipes were deemed sufficient based on data analysis and domain knowledge, providing a balance between comprehensiveness and accuracy. The second assumption involves iterative experimentation with different model-recipe combinations, using accuracy and ROC metrics for evaluation to assess each combination's effectiveness. The third assumption is that nominal predictor variables are converted to dummy variables, excluding the target variable, and variables with zero variance are removed to simplify the model. Lastly, since BMI, the target variable, is derived from height and weight, these variables are crucial for prediction. Cross-validation was performed by dividing the training data into 10 folds to ensure robust model evaluation. Each workflow was tested on all folds to guarantee comprehensive validation, with the performance of each model-recipe combination ranked in Table 6.

Table 6 presents the performance metrics of different models during cross-validation, including the mean and standard error of accuracy and receiver operating characteristic area under the curve (ROC AUC). Illustrated below with the first row as an example. In addition, to improve the interpretability of these findings, a graphical representation is shown in Figure 8. The 'workflow id' specifies the model and recipe combination, such as 'smaller_set_multilogit', which uses a multinomial logistic regression model with a smaller set of features (Recipe 2). Key evaluation metrics include accuracy and ROC AUC. The 'Mean' values reflect average performance across cross-validation folds, with accuracy at approximately 97.02% and ROC AUC around 99.64%. The 'Std_err' (Standard Error) measures the variability of these averages, where smaller values imply more reliable estimates. In this case, accuracy has a standard error of 0.69%, and ROC AUC has 0.14%. The 'model' column identifies the ML model used, 'multinom_reg' for multinomial logistic regression. The 'rank' column indicates the workflow's performance relative to others, with a rank of 1 signifying the highest performance. The multinomial logistic regression model with a smaller set of features ranks first for both accuracy and ROC AUC, underscoring the benefits of focusing on a reduced set of variables for improved performance. This trend was also observed in models such as Random Forest, SVM, and Decision

TABLE 6 | Ranking of the workflows.

Workflow ID	Metrics	Mean (%)	Std_err (%)	Model	Rank
smaller_set_multilogit	accuracy	97.02	0.69	multinom_reg	1
smaller_set_multilogit	roc_auc	99.64	0.14	multinom_reg	1
all_features_multilogit	accuracy	95.32	0.50	multinom_reg	2
all_features_multilogit	roc_auc	99.62	0.10	multinom_reg	2
smaller_set_svm	accuracy	94.51	0.81	svm_linear	3
smaller_set_svm	roc_auc	99.49	0.08	svm_linear	3
smaller_set_rforest	accuracy	91.67	0.90	rand_forest	4
smaller_set_rforest	roc_auc	99.38	0.08	rand_forest	4
all_features_svm	accuracy	93.15	0.86	svm_linear	5
all_features_svm	roc_auc	99.36	0.09	svm_linear	5
all_features_rforest	accuracy	91.73	0.79	rand_forest	6
all_features_rforest	roc_auc	99.35	0.09	rand_forest	6
smaller_set_dtree	accuracy	87.19	1.14	decision_tree	7
smaller_set_dtree	roc_auc	96.73	0.34	decision_tree	7
all feasures_dtree	accuracy	87.39	1.10	decision_tree	8
all feasures_dtree	roc_auc	96.70	0.34	decision_tree	8
all_features_naiveBayes	accuracy	57.08	1.87	naive_Bayes	9
all_features_naiveBayes	roc_auc	92.70	0.35	naive_Bayes	9
smaller_set_naiveBayes	accuracy	52.81	1.37	naive_Bayes	10
smaller_set_naiveBayes	roc_auc	92.10	0.32	naive_Bayes	10

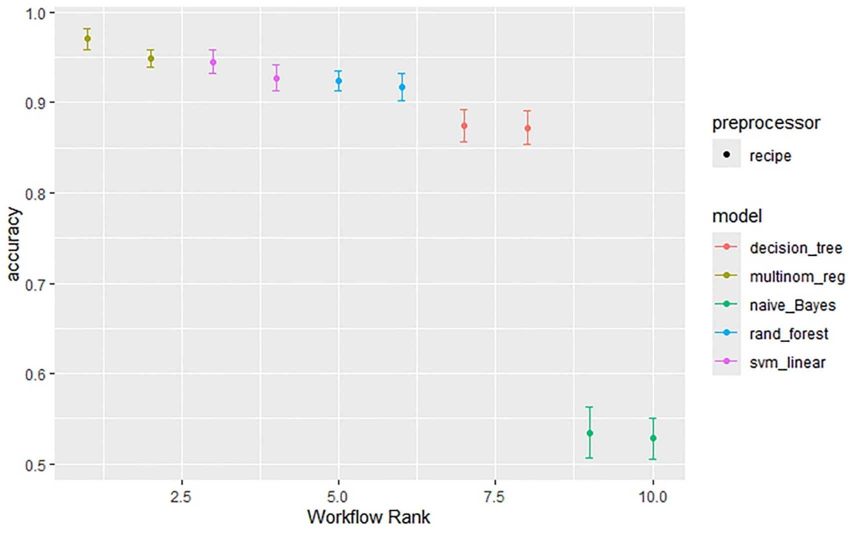

FIGURE 8 | Workflow ranking with accuracy.

Tree, though Decision Tree's relatively lower performance reflects its simplicity and tendency to overfit. Naïve Bayes, which ranks lowest in accuracy, due to its assumption of feature independence, which fails to capture the complex, interrelated factors affecting obesity levels, as evidenced by the positive correlation between height and weight.

6.1.4 | Train the Model

From the previous phase, it has been proven that the combination of the multinomial logistic regression model and Recipe 2 performed best. Therefore, an optimal workflow that encapsulates those two, which is used for predicting obesity levels.

This encapsulation provides a more structured and organised framework for the predictive model, enhancing the modularity of the system. After establishing the workflow, the model fits using the training data. This fitted model can after being used to make predictions on new data or assess its performance on testing datasets as illustrated in Figure 9.

6.1.5 | Predictive Model Performance Metrics

After fitting the model on the training set, the testing set is used for validation. Table 7 presents the confusion matrix of the obesity predictive model, from which accuracy, precision, recall, and $F1$-scores were calculated. The blue highlighted numbers in the confusion matrix represent the correct predictions made by the model, where the predicted class matches the true (actual) class. The resulting performance metrics are summarised in Table 8, while the AUC result is illustrated in Figure 10.

$$\text{Accuracy} = \frac{\text{Sum of the Correct Predictions}}{\text{Total Numbe of Predictions}} = \frac{(\text{TP} + \text{TN})}{\text{TP} + \text{TN} + \text{FN} + \text{FN}},$$

$$\text{Precision} = \frac{\text{The Ratio of TP Predictions}}{\text{The Total Number of Positives Predictions}} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$

$$\text{Recall (Sensitivity)} = \frac{\text{The Ratio of TP Predictions}}{\text{The Total Number of Actual Positive Instances}} = \frac{\text{TP}}{\text{TP} + \text{FN}},$$

$$F1\text{-Scores} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$

As shown in Table 8, the model trained in this study demonstrates high accuracy, achieving 97.48%. Additionally, the precision, recall and $F1$ Score all exceed 97%. Regarding AUC, both the normal weight and Obesity Level II categories reached 100%, while the remaining categories achieved 99%. In summary, these results demonstrate the effectiveness of the expert system in accurately diagnosing obesity conditions.

Although achieving high accuracy is a fundamental goal in model development, it is not the sole criterion in clinical applications. Interpretability is equally critical, as physicians must understand the rationale behind predictions to trust the expert system's results and effectively apply them in clinical decision-making. Therefore, an optimal model must balance both accuracy and interpretability to be practically useful in healthcare settings. Moreover, we argue that interpretability should be considered an essential aspect of model accuracy, as a model, regardless of its interpretability, remains unsuitable for clinical diagnosis if it does not achieve high predictive performance.

Among the selected models, multinomial logistic regression demonstrated the best performance. It is widely used in medical applications due to its inherent interpretability. Unlike black-box models such as SVM and random forest, multinomial logistic regression provides clear probabilistic explanations for classification outcomes. By predicting six distinct obesity levels and assigning corresponding probability estimates to each classification, multinomial logistic regression enhances the interpretability of predictions, allowing doctors to better understand and trust the model's decision-making process. This interpretability is essential for integrating predictive modelling

TABLE 8 | Performance metrics of the model.

Metric	Estimation
Accuracy	0.9748428
Precision	0.9758040
Recall	0.9743645
f_meas ($F1$ score)	0.9749602

```
```{r}
obesity_wflow_optimal <-
  workflow() %>%
  add_model(multinom_reg_nnet_spec) %>%
  add_recipe(obesity_recipe_2)

```
```

```
```{r}
obesity_fit <-
  obesity_wflow_optimal %>%
  fit(data = train_data)

```
```

FIGURE 9 | Fit model.

TABLE 7 | Confusion matrix of the model.

	Truth					
Prediction	**Underweight**	**Normal weight**	**Overweight**	**Obesity_I**	**Obesity_II**	**Obesity_III**
Underweight	79	3	0	0	0	0
Normal weight	2	90	1	0	0	0
Overweight	0	0	167	5	0	0
Obesity_I	0	0	1	105	1	0
Obesity_II	0	0	0	2	102	1
Obesity_III	0	0	0	0	0	77

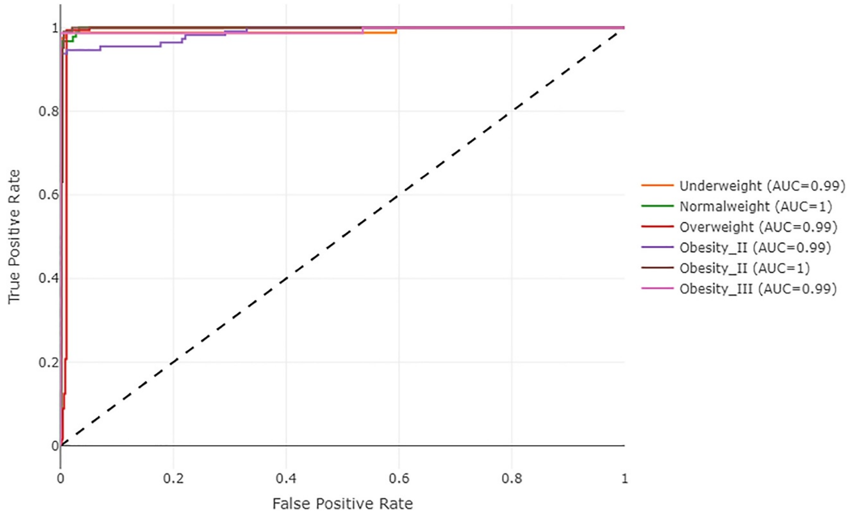

FIGURE 10 | Area under the ROC curve for obesity levels.

into clinical practice, ensuring both reliability and confidence in data-driven medical decision-making.

6.2 | Expert System and Web Application for Treatment Recommendations

This section proves the research results that integrating the ML model into R Shiny to create a novel expert system for diagnosing obesity levels. Although the previous section focused on constructing the predictive model, which represents the prediction phase within the system architecture, this section emphasises the recommendation phase. This aligns with the study's objectives, ensuring a comprehensive approach to obesity diagnosis and management.

6.2.1 | Web Application: Treatment Recommendations for Obesity

Attachment 1 presents the web application interface designed for obesity assessment and treatment recommendations. This expert system comprises three main modules: system introduction, obesity assessment and obesity results. Upon entering the application, users are greeted with the system introduction page, which provides essential information on the obesity risks, classification levels, the limitations of the conventional BMI-based evaluation and the advantages of the proposed system. The system ensures that users can assess their health status while maintaining their privacy. Additionally, detailed navigation instructions are provided to facilitate a seamless user experience. After reviewing this section, users can proceed to the assessment module by clicking the 'Evaluate it now!' button. In the obesity assessment phase, users are prompted to answer 12 questions, corresponding to the reduced feature set (Recipe 2). Once responses are submitted, the system generates predictions by clicking 'Click me!', determining the user's obesity classification. During the obesity results phase, the system presents two key components: an orange warning area that displays the predicted obesity level along with its associated probability. Given that the model generates a probability distribution across multiple obesity categories, probability values are sorted in descending order, and only the highest probability classification is displayed on the user interface. A suggestion area, where personalised treatment recommendations are provided based on the predicted obesity level. To enhance clarity and usability, users can only view their most probable classification, ensuring they receive the most relevant and meaningful diagnosis. However, healthcare professionals and system administrators have access to complete probability distribution, enabling a more comprehensive evaluation. The system's recommendations follow an 'if-then' rule-based framework, tailoring guidance based on the predicted obesity classification. These recommendations are derived from authoritative sources, including peer-reviewed medical literature and expert advice, ensuring that users receive evidence-based and clinically relevant guidance. By integrating transparent predictive modelling and structured treatment recommendations, the expert system provides a reliable and interpretable tool for obesity assessment and management.

6.2.2 | Expert System Evaluation

The evaluation of the expert system encompassed an assessment of its accuracy and sensitivity, both of which matched those of the predictive model at 97.48% and 97.44%, respectively, demonstrating the system's strong capability to distinguish between various obesity levels effectively. Additionally, a user satisfaction survey was conducted with a diverse group of participants to evaluate various aspects of the system. The survey included questions related to functionality, interface design, user experience, and perceived accuracy. Key area of inquiry involved the proper functioning of all system features, the visual appeal and intuitiveness of the interface, ease of navigation, clarity of instructions, and overall user trust and satisfaction. The feedback from these responses will be systematically analysed to refine and enhance the system, ensuring it aligns with user expectations and contributes to improved future health assessments.

7 | Conclusion and Discussion

This section begins with a comprehensive comparative analysis, examining the results obtained in this study in relation to existing findings from the literature. It then critically reviews the limitations of this research and offers insightful suggestions for future studies. Finally, it summarises the main findings of this paper and discusses the implications for healthcare.

To demonstrate the potential and advantages of this novel expert system for obesity diagnosis and treatment recommendations, a comparative analysis with related studies in this field is essential. Currently, an increasing number of research efforts focus on diagnosing obesity levels, leveraging ML models and AI-based expert systems. However, after reading many research papers, few studies were found that specifically align with this research on obesity level diagnosis. As a result, the scope of comparison was broadened to include expert systems developed for other disease diagnoses. Table 9 provides a comparative summary of this study against other related works, based on specific parameters. The comparison primarily focuses on the predictive model, the accuracy of the expert system or model, the existence of an expert system or application, and the inclusion of treatment recommendations. The comparative analysis demonstrates that the proposed expert system, utilising multinomial logistic regression, achieves a high diagnostic accuracy of 97.48%, outperforming several existing methods, including decision tree, random forest and hybrid models. Unlike previous works that focus solely on predictive accuracy, this system provides actionable treatment recommendations, addressing a crucial gap in obesity diagnosis and management. Comparatively, Albadrasawi et al. [31] also incorporating an expert system and treatment recommendations, however, the decision tree model is not as effective as ours. Additionally, random forest models have been widely applied in other studies, demonstrating accuracy levels ranging from 72.76% to 98.99%. Among these, only Prawira Putra et al. [40] integrate an expert system, while none provide diagnostic recommendations. A hybrid model approach, as seen in Solomon et al. [29], achieved 97.16% accuracy but does not incorporate an expert system or diagnostic recommendations. The study by Gozukara Bag et al. [28] reports the highest accuracy of 98.99% among all reviewed works but does not include an expert system or diagnostic recommendations. Overall, while many studies achieve high accuracy using different machine learning models, the integration of expert systems and diagnostic recommendations remains limited. Our proposed expert system distinguishes itself as a valuable tool in healthcare, not only for its diagnostic reliability but also for its potential to improve treatment outcomes, particularly in underserved populations. Therefore, this research contributes a novel and practical approach to enhancing clinical decision-making and personalised patient care.

Although this study makes a novel contribution to healthcare through a comparative analysis of results, it has certain limitations. The effectiveness and accuracy of expert systems largely depend on the availability and quality of data. Because of the constraints of the original dataset, the dataset used in this study comprises both real user data and synthetic data generated to address class imbalance issues. To enhance the system's reliability and ensure its effectiveness in real-world applications, future improvements will focus on integrating a comprehensive database into the expert system. This database will continuously store user data upon entry, facilitating the incorporation of a larger proportion of real user data, particularly longitudinal health records related to dietary habits and physical conditions. Such an approach will enable continuous monitoring and improve predictive accuracy. Furthermore, by tracking and recording users' obesity levels over time, the expert system could visually display obesity trends within its interface, allowing users to monitor their long-term progress more effectively. Another limitation of this study is that the dataset relies on BMI to define obesity levels, a commonly used but imperfect metric, as it overlooks factors such as muscle mass, fat distribution and body composition. Therefore, future improvements will incorporate additional quantitative variables, such as WC, WHR and WHtR, to provide a more nuanced assessment of obesity risk. In

TABLE 9 | Comparative analysis of results.

Article	Best model	Accuracy	Availability of expert system or application	Recommendations for diagnostic results
This work	Multinomial logistic regression	97.48%	Yes	Yes
[31]	Decision tree	Sensitivity: 92% specificity: 95%	Yes	Yes
[32]	—	MSE: 0.388%	Yes	No
[39]	Decision tree	97.4%	Yes	No
[40]	Random forest	92.25%	Yes	No
[28]	Random forest	98.99%	No	No
[29]	Hybrid model	97.16%	No	No
[30]	Random forest	78%	No	No
[27]	Random forest	72.76%	No	No
[41]	Random forest	96%	No	No

addition, a new method for calculating target variables will be developed based on expert recommendations regarding feature weighting, further refining the predictive framework. Finally, exploring advanced ML models such as Gradient Boosting Machines and Neural Networks will further refine model accuracy and ensure the expert system remains innovative and effective.

In summary, this study successfully developed an innovative expert system for diagnosing and predicting obesity levels while providing tailored treatment recommendations. The SEMMA data mining process guided the systematic progression from raw data to a functional predictive model, leveraging R language for model construction and R Shiny for user interface design. Data preprocessing ensured the dataset was clean and consistent, and exploratory data analysis established a solid foundation for model input variables. Five multi-classification ML algorithms—multinomial logistic regression, decision tree, random forest, SVM and Naive Bayes—were employed. Among these, the multinomial logistic regression model, with a smaller set of features, achieved an impressive accuracy of 97.48%. The R Shiny-based web application feature consists of three core modules: system introduction, obesity assessment, and results presentation, delivering interactive and user-friendly functionality. Additionally, treatment recommendations are generated using expert knowledge and if-then rules tailored to individual assessments. Feedback from user satisfaction surveys facilitated iterative improvements to the system's usability and interface. Comparative analysis demonstrated that the expert system outperforms existing methods in accuracy and diagnostic reliability, affirming its effectiveness as a robust tool for prediction and diagnosis. The developed expert system represents a transformative advancement in healthcare, specifically in diagnosing and providing treatment recommendations for obesity. By enabling early detection, the system allows individuals to become aware of their obesity risk and receive professional treatment advice before their condition progresses. Early intervention has the potential to reverse obesity trends, offering a more effective and cost-efficient solution compared to treating advanced stages. Given that obesity is often linked to chronic diseases, the widespread adoption of this expert system could significantly enhance public health management. Moreover, its integration into healthcare infrastructure, particularly in underserved rural areas, extends accessibility and education, empowering individuals to make informed health decisions and improve their overall well-being.

Acknowledgements

This research was supported by the National Research, Development and Innovation Office (NKFIH) under Grant 2024-1.2.3-HU-RIZONT-2024-00030.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.