Machine Learning-Based Obesity Classification: A Comparative Study Using Self-Reported Survey Data and Ensemble Learning Models

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Abstract

Obesity has become one of the most pressing global health challenges of the 21st century, with its prevalence increasing at an alarming rate. Obesity is a major global health concern, contributing to an increased risk of cardiovascular disease, diabetes, and other metabolic disorders. Traditional assessment methods, such as BMI-based classification, often fail to incorporate lifestyle and behavioral factors, limiting their predictive capabilities. This study explores the use of machine learning for obesity classification based on self-reported survey data collected from individuals in Mexico, Peru, and Colombia. The dataset comprises 2111 instances with 17 attributes, covering demographic characteristics, eating habits, and physical activity levels. Eight machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors, Naïve Bayes, and AdaBoost, were evaluated using 10-fold cross-validation. Results indicate that Gradient Boosting achieved the highest accuracy of 96.49%, followed by Random Forest and SVM, demonstrating the effectiveness of ensemble learning techniques in capturing complex feature interactions. In contrast, Naïve Bayes and AdaBoost exhibited the lowest classification performance due to their strong assumptions about feature independence and sensitivity to noisy data. The findings highlight the potential of machine learning in obesity classification and underscore the need for advanced predictive models to enhance public health monitoring and intervention strategies.

Keywords: *Obesity Classification, Machine Learning, Ensemble Learning, Self-Reported Survey Data, Health Informatics*

Abstrak

Obesitas telah menjadi salah satu tantangan kesehatan global yang paling mendesak di abad ke-21, dengan prevalensinya meningkat pada tingkat yang mengkhawatirkan. Obesitas merupakan masalah kesehatan global yang utama, yang berkontribusi terhadap peningkatan risiko penyakit kardiovaskular, diabetes, dan gangguan metabolik lainnya. Metode penilaian tradisional, seperti klasifikasi berbasis BMI, sering kali gagal menggabungkan faktor gaya hidup dan perilaku, sehingga membatasi kemampuan prediktifnya. Studi ini mengeksplorasi penggunaan pembelajaran mesin untuk klasifikasi obesitas berdasarkan data survei yang dilaporkan sendiri yang dikumpulkan dari individu di Meksiko, Peru, dan Kolombia. Kumpulan data terdiri dari 2111 contoh dengan 17 atribut, yang mencakup karakteristik demografi, kebiasaan makan, dan tingkat aktivitas fisik. Delapan model pembelajaran mesin, termasuk Regresi Logistik, Hutan Acak, Peningkatan Gradien, Mesin Vektor Dukungan (SVM), Pohon Keputusan, K-Nearest Neighbors, Naïve Bayes, dan AdaBoost, dievaluasi menggunakan validasi silang 10 kali lipat. Hasil penelitian menunjukkan bahwa Gradient Boosting mencapai akurasi tertinggi sebesar 96,49%, diikuti oleh Random Forest dan SVM, yang menunjukkan efektivitas teknik pembelajaran ensemble dalam menangkap interaksi fitur yang kompleks. Sebaliknya, Naïve Bayes dan AdaBoost menunjukkan kinerja klasifikasi terendah karena asumsi mereka yang kuat tentang independensi fitur dan sensitivitas terhadap data yang bising. Temuan tersebut menyoroti potensi pembelajaran mesin dalam klasifikasi obesitas dan menggarisbawahi perlunya model prediktif tingkat lanjut untuk meningkatkan pemantauan kesehatan masyarakat dan strategi intervensi.

Kata Kunci: Klasifikasi Obesitas, Pembelajaran Mesin, Pembelajaran Ensemble, Data Survei yang Dilaporkan Sendiri, Informatika Kesehatan

INTRODUCTION

Obesity has become one of the most pressing global health challenges of the 21st century, with its prevalence increasing at an alarming rate (Koliaki, Dalamaga, & Liatis, 2023; Mohajan & Mohajan, 2023; Ryan, Barquera, Barata Cavalcanti, & Ralston, 2021). The World Health Organization (WHO) reports that since 1975, obesity has nearly tripled worldwide, with approximately 1.9 billion adults classified as overweight and over 650 million classified as obese as of 2016 (Awotunde, 2021; Conde, Silva, & Ferraz, 2022; Hojjat & Hojjat, 2021). This condition is not merely a cosmetic concern but a complex metabolic disorder associated with severe health complications, including cardiovascular diseases (CVD), type 2 diabetes, hypertension, stroke, osteoarthritis, and various types of cancer (Guła et al., 2024; Keramat et al., 2021; Kim & Lee, 2023). The economic burden of obesity is also substantial, leading to increased healthcare costs, reduced workforce productivity, and higher mortality rates (Hecker, Freijer, Hiligsmann, & Evers, 2022; Menon et al., 2022; Sweis, 2024). Addressing obesity requires an improved understanding of its determinants, early diagnosis, and the development of effective intervention strategies.

Traditionally, obesity is assessed using clinical and anthropometric measurements such as Body Mass Index (BMI), waist-to-hip ratio, and body fat percentage (Moltrer et al., 2022). BMI, which is calculated by dividing a person's weight (in kilograms) by the square of their height (in meters), is the most widely used metric for obesity classification (Heymsfield et al., 2025). However, BMI has several limitations, including its inability to distinguish between fat mass and muscle mass, as well as its failure to consider individual metabolic variations and lifestyle factors (Pluta, Dudzińska, & Lubkowska, 2022). Moreover, other obesity assessment techniques, such as dual-energy X-ray absorptiometry (DEXA) scans and bioelectrical impedance analysis, are often expensive and not readily accessible for large-scale population screening (Thomas et al., 2025). Consequently, there is a growing interest in developing alternative, non-invasive, and scalable methods for obesity classification.

Recent advances in machine learning (ML) have opened new avenues for obesity classification and risk assessment. Unlike traditional statistical models, which rely on predefined assumptions, ML algorithms can automatically learn patterns and relationships from data, enabling more accurate and flexible classification (Albahra et al., 2023). These models have been successfully applied in various healthcare applications, including early disease detection, personalized medicine, and predictive analytics (Hassan et al., 2022). Specifically, ML has shown promising results in obesity-related studies by leveraging clinical, biometric, and behavioral data to predict weight status and associated health risks (Feretzakis et al., 2024). However, despite the significant progress in ML-based obesity research, most existing studies primarily focus on datasets derived from medical records or genetic predispositions, overlooking the potential of self-reported lifestyle and behavioral data (Kassem et al., 2025).

This study aims to fill this gap by applying ML models to classify obesity levels using self-reported survey data collected from individuals across Mexico, Peru, and Colombia. The dataset consists of 2111 records with 17 attributes covering demographic characteristics, eating habits, and physical activity levels. These features include gender, age, food consumption frequency, alcohol intake, smoking habits, transportation methods, and screen time. The dataset represents a diverse sample of individuals aged between 14 and 61, allowing for a broader analysis of obesity determinants across different age groups. By utilizing this dataset, our study seeks to evaluate the predictive capabilities of different ML classifiers in obesity classification and compare their performance across multiple evaluation metrics.

We employ a range of ML classification models, including Logistic Regression, Random Forest, Gradient Boosting, AdaBoost, Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), and Naïve Bayes. Each model is trained using a 10-fold stratified cross-validation technique to ensure robust performance evaluation. The models are assessed based on key classification metrics such as accuracy, precision, recall, and F1-score. The primary objective of this research is to determine which ML algorithms perform best in obesity classification when applied to self-reported lifestyle and behavioral data.

This study is unique in its approach, as it demonstrates the feasibility of using self-reported survey data for obesity classification. Traditional obesity assessments require medical testing and clinical consultations, which may not always be practical for large-scale screening, particularly in resource-limited settings. By contrast, survey-based classification models provide a cost-effective and scalable alternative for early detection and risk assessment. If successful, this approach could be integrated into digital health applications, enabling individuals to assess their obesity risk using mobile-based health surveys and receive personalized recommendations based on their lifestyle patterns.

Furthermore, understanding the role of different lifestyle and behavioral factors in obesity classification is crucial for designing targeted public health interventions. By identifying the most influential predictors of obesity, healthcare policymakers and nutritionists can develop personalized obesity prevention programs that encourage healthy eating habits, promote physical activity, and raise awareness about modifiable risk factors. Additionally, this study provides insights into the interpretability of different ML models, highlighting the advantages and limitations of each approach in obesity classification. The remainder of this paper is structured as follows: Section 2 presents the dataset, preprocessing steps, and ML models used in this study. Section 3 details the experimental results, comparing the performance of different classifiers and discusses the implications of the findings, including their potential applications and limitations. Finally, Section 4 concludes the study and outlines future research directions.

METHOD

The methodology employed in this study follows a systematic process, beginning with dataset description, data preprocessing, machine learning model selection, and performance evaluation using statistical and computational techniques and can be downloaded from (PCoder, 2024). The dataset utilized in this research consists of survey-based obesity classification data collected from individuals in Mexico, Peru, and Colombia. This dataset comprises 2111 instances with 17 attributes, encompassing demographic characteristics such as gender, age, height, and weight, as well as lifestyle and behavioral features, including eating habits, physical activity levels, and transportation modes. The target variable represents obesity levels and is categorized into six distinct classes, where each class corresponds to a standard Body Mass Index (BMI) classification. The categories include underweight for individuals with a BMI less than 18.5, normal weight for those with a BMI ranging from 18.5 to 24.9, overweight for BMI values between 25.0 and 29.9, obesity class I for BMI values between 30.0 and 34.9, obesity class II for BMI values between 35.0 and 39.9, and obesity class III for individuals with BMI values equal to or greater than 40.0. These classifications serve as the labels for the supervised machine learning models used in this study.

To ensure the quality and reliability of the data before model training, a series of preprocessing steps are applied. Missing values, which often arise in real-world survey datasets, are addressed using different imputation strategies based on the nature of the variable. Numerical features with missing values are imputed using the mean of the respective attribute, ensuring that the overall distribution of the dataset remains unchanged. For categorical features, missing values are replaced by the mode, selecting the most frequently occurring category within that attribute. This imputation strategy preserves the integrity of categorical distributions while maintaining consistency across the dataset. After handling missing values, categorical features are encoded into numerical representations using label encoding, where each unique category is assigned a distinct integer value. Formally, given a categorical feature (X_j) with possible values ($\{v_1, v_2, \ldots, v_K\}$), label encoding assigns an integer \(k\) to each category such that ($X_j = k$), where (v_k) is the category index. This transformation ensures compatibility with machine learning models while maintaining categorical relationships. Once categorical features are encoded, numerical features undergo standardization to ensure equal weighting across different attributes. Standardization transforms each numerical attribute by subtracting the mean and dividing by the standard deviation. Mathematically, for a feature (X_j), the standardized value is given by (1).

$$X'_j = \frac{X_j - \mu_j}{\sigma_j}$$

where (μ_j) represents the mean and (σ_j) represents the standard deviation, calculated as (2).

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} X_{ij}, \quad \sigma_j = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{ij} - \mu_j)^2}$$

This normalization process ensures that all features contribute equally to the classification models, preventing attributes with large numerical ranges from disproportionately influencing model training. Following preprocessing, multiple supervised machine learning models are implemented to classify obesity levels based on survey responses. Logistic regression is employed as a baseline model, utilizing the softmax function to predict the probability of each obesity class. Given an input feature vector (X), the probability of belonging to class (C_k) is computed as (3).

$$P(y = C_k|X) = \frac{\exp(W_k^T X + b_k)}{\sum_{j=1}^{6} \exp\left(W_j^T X + b_j\right)}$$

where (W_k) and (b_k) denote the weight vector and bias term for class (C_k), respectively. Additionally, ensemble learning techniques are incorporated, including random forest and gradient boosting. The random forest classifier constructs multiple decision trees and aggregates their predictions through majority voting, expressed as (4).

$$\hat{y} = \arg\max_k \sum_{t=1}^{T} h_t(X)$$

where ($h_t(X)$) represents the prediction from the (t)-th decision tree. The gradient boosting model, on the other hand, improves classification accuracy by sequentially training weak learners, optimizing for classification error at each stage. The formulation of the gradient boosting model at iteration (m) is given by (5).

$$F_m(X) = F_{m-1}(X) + \gamma_m h_m(X)$$

where $(F_m(X))$ is the updated model, $(h_m(X))$ is the weak learner at iteration (m), and (γ_m) is the learning rate controlling the contribution of each new weak learner. The AdaBoost classifier is also employed, where misclassified samples are assigned higher weights in subsequent iterations, and the weight update rule is given by (6).

$$\alpha_m = \frac{1}{2}\ln\left(\frac{1-e_m}{e_m}\right)$$

where (e_m) represents the classification error at iteration (m). Other models implemented in this study include support vector machines, which identify an optimal hyperplane that maximizes the margin between classes, mathematically defined as (7).

$$\max_{w,b} \quad \frac{1}{|w|}\sum_{i=1}^{N} y_i(w^T X_i + b) \geq 1$$

The k-nearest neighbors classifier assigns class labels based on the majority vote among the (k) nearest neighbors, formulated as (8).

$$y = \arg\max_k \sum_{i \in \mathcal{N}_k} \mathbb{1}(y_i = C_k)$$

where $(\mathcal{N}_k)$ denotes the set of (k) nearest neighbors in feature space. The Naïve Bayes classifier, which assumes feature independence, computes the probability of each class using Bayes' theorem as (9).

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

The evaluation of these models is conducted using 10-fold stratified cross-validation, ensuring that the class distribution is preserved across training and validation sets. For each fold, the model is trained on 90\% of the data and validated on the remaining 10\%, and this process is repeated ten times to obtain an averaged performance score. The performance of each classification model is assessed using multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The accuracy of a given model is defined as (10).

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} \mathbb{1}(\hat{y}_i = y_i)}{N}$$

where $(\mathbb{1}(\hat{y}_i = y_i))$ is an indicator function that equals 1 if the predicted class $(\hat{y}_i)$ matches the true class (y_i). Precision is calculated as (11).

$$\text{Precision} = \sum_{k=1}^{6} \frac{TP_k}{TP_k + FP_k} \times \frac{N_k}{N}$$

while recall is given by (12).

$$\text{Recall} = \sum_{k=1}^{6} \frac{TP_k}{TP_k + FN_k} \times \frac{N_k}{N}$$

The F1-score, which provides a harmonic mean between precision and recall, is computed as (13).

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

RESULTS AND DISCUSSION

As presented in the table 1 and figure 1, the results indicate that Gradient Boosting achieved the highest overall performance, with an accuracy of 96.49% and an F1-score of 96.39%. This suggests that boosting techniques are highly effective in capturing complex patterns within the dataset. The Random Forest classifier also performed well, obtaining an accuracy of 95.36% and an F1-score of 95.63%. The slightly lower performance compared to Gradient Boosting may be attributed to the lack of sequential learning, as Random Forest constructs trees independently rather than iteratively refining weak learners. However, both ensemble methods outperform other classifiers, highlighting the strength of tree-based models in obesity classification.

Support Vector Machine also exhibited strong performance, achieving an accuracy of 95.40% and an F1-score of 95.39%. This result suggests that SVM effectively separates obesity categories within the feature space, likely due to its ability to maximize the decision margin. The performance of SVM is comparable to that of Random Forest, demonstrating its robustness in handling non-linear relationships within the dataset. Decision Tree classification achieved slightly lower performance than its ensemble counterparts, with an accuracy of 93.61% and an F1-score of 93.55%. While Decision Trees provide interpretability and computational efficiency, they are prone to overfitting, which may explain the reduced generalization performance compared to Random Forest and Gradient Boosting.

Logistic Regression achieved an accuracy of 88.44% and an F1-score of 88.32%. This result demonstrates that logistic regression is capable of modeling linear relationships between features and obesity categories but lacks the complexity required to achieve higher predictive performance. The K-Nearest Neighbors classifier achieved an accuracy of 82.00%, which is lower than decision tree-based methods. This decline in performance may be attributed to the curse of dimensionality, where distance-based algorithms struggle to maintain discriminatory power in high-dimensional feature spaces. Naïve Bayes performed significantly worse than other models, with an accuracy of 59.31% and an F1-score of 56.15%. The poor performance of Naïve Bayes can be attributed to its assumption of feature independence, which does not hold in this dataset, as obesity is influenced by multiple interdependent factors such as dietary habits, physical activity, and body measurements. AdaBoost exhibited the lowest classification performance, achieving an accuracy of only 45.43% and an F1-score of 38.56%. This result indicates that AdaBoost struggles with complex class distributions and may be highly sensitive to noise within the dataset.

Table 1. Machine Learning Performance

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.884414	0.887356	0.884414	0.883202
Random Forest	0.953577	0.958052	0.954996	0.956321
Gradient Boosting	0.964949	0.965717	0.964949	0.963892
AdaBoost	0.454279	0.422626	0.454279	0.385607
Support Vector Machine	0.954042	0.956533	0.954042	0.953928
Decision Tree	0.936052	0.93891	0.935576	0.935517
K-Nearest Neighbors	0.819986	0.817259	0.819986	0.811738
Naive Bayes	0.593074	0.628485	0.593074	0.561476

The comparative performance of these models suggests that ensemble learning methods, particularly Gradient Boosting and Random Forest, are the most effective for obesity classification. Their ability to aggregate multiple weak learners and refine decision boundaries contributes to superior generalization performance. Support Vector Machine also provides a strong alternative, particularly for datasets with well-separated class structures. In contrast, simpler models such as Logistic Regression, K-Nearest Neighbors, and Naïve Bayes demonstrate limitations in handling intricate feature interactions, making them less suitable for this classification task. The relatively low performance of AdaBoost suggests that boosting algorithms that rely on sequential re-weighting may be ineffective in this specific dataset. This could be due to the nature of the obesity classification problem, where small changes in feature weighting do not significantly impact the class separability. Additionally, the lower performance of Naïve Bayes highlights the limitations of assuming feature independence in complex health-related datasets. The findings of this study demonstrate that tree-based ensemble models significantly outperform other classifiers in obesity classification using survey data. The ability of these models to handle non-linear feature interactions and provide high predictive accuracy makes them highly suitable for applications in health monitoring and early obesity risk assessment. The insights gained from this analysis can guide future research in optimizing classification models for obesity prediction, particularly through the integration of hybrid approaches that combine multiple learning paradigms.

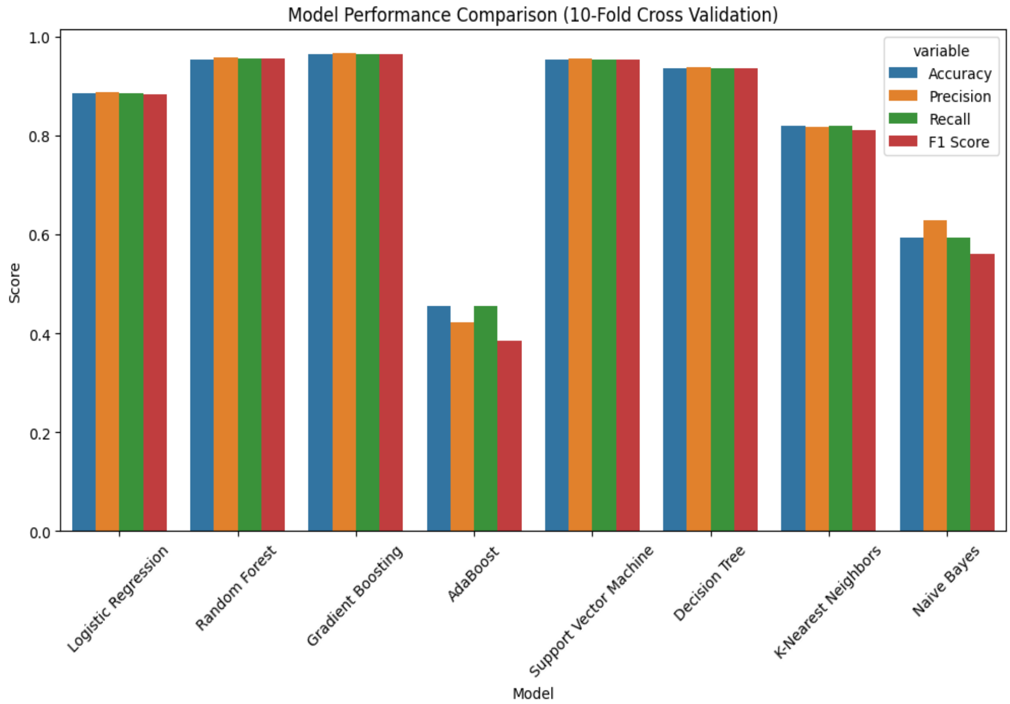

Figure 1. Performance Results of Machine Learning Models

CONCLUSIONS AND RECOMMENDATIONS

This study investigated the application of various machine learning models for obesity classification using self-reported survey data. The dataset, collected from individuals in Mexico, Peru, and Colombia, contained demographic, lifestyle, and dietary attributes. Through rigorous preprocessing steps, including handling missing values, encoding categorical variables, and feature scaling, the dataset was prepared for classification using eight different machine learning algorithms. The performance of these models was evaluated using a 10-fold cross-validation approach, with accuracy, precision, recall, and F1-score as the primary evaluation metrics.

The results demonstrated that Gradient Boosting achieved the highest classification performance, with an accuracy of 96.49%, followed closely by Random Forest and Support Vector Machine (SVM), both of which exhibited robust predictive capabilities. The effectiveness of these models can be attributed to their ability to capture non-linear relationships and intricate feature interactions. Decision Tree also performed well but was slightly less effective due to its tendency to overfit the training data. Logistic Regression provided moderate performance, suggesting that linear classification models, while interpretable, lack the complexity required for highly accurate obesity classification. K-Nearest Neighbors (KNN) demonstrated a moderate level of performance but was affected by the curse of dimensionality, reducing its predictive capability in high-dimensional spaces. Conversely, Naïve Bayes performed poorly, with an accuracy of 59.31%, which was expected given its strong assumption of feature independence. Since obesity classification involves multiple interdependent factors, the conditional independence assumption was not suitable for this dataset. AdaBoost, which typically enhances weak learners, exhibited the lowest performance, achieving an accuracy of only 45.43%. The poor performance of AdaBoost suggests that boosting methods requiring precise feature weight adjustments may struggle with complex class distributions, particularly in datasets with overlapping feature spaces.

The findings of this study highlight the superiority of ensemble learning techniques such as Gradient Boosting and Random Forest in obesity classification tasks. Their ability to combine multiple weak learners and refine decision boundaries contributed significantly to their superior generalization capabilities. Support Vector Machine also proved to be a strong contender, showcasing its effectiveness in handling high-dimensional classification problems. These results emphasize that obesity classification benefits from models that can capture intricate feature dependencies rather than those relying on linear separability or simplistic probabilistic assumptions. The insights gained from this research have significant implications for public health monitoring and early intervention strategies. By leveraging machine learning models, healthcare professionals can develop automated screening tools to identify individuals at risk of obesity and associated metabolic disorders. This approach can facilitate personalized health recommendations, enabling early-stage interventions that promote healthy lifestyle modifications. Furthermore, the use of self-reported survey data underscores the feasibility of low-cost, scalable obesity prediction models, which could be integrated into mobile health applications and digital health platforms.

Despite the promising results, several limitations of this study must be acknowledged. First, the dataset was based on self-reported survey responses, which are subject to biases such as underreporting or overreporting of dietary habits and physical activity. Future studies should consider integrating objective health data, such as biometric measurements and medical records, to enhance classification accuracy. Second, while this study focused on traditional machine learning classifiers, deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), could be explored for more advanced feature extraction and sequence-based learning. Additionally, feature selection techniques could be implemented to improve model interpretability and computational efficiency. For future work, integrating real-time health monitoring data from wearable devices could enhance the predictive capabilities of machine learning models by providing continuous insights into lifestyle behaviors. The incorporation of explainable AI (XAI) techniques could also improve trust and adoption by healthcare practitioners by offering interpretable obesity predictions. Finally, expanding the dataset to include more diverse populations and larger sample sizes would ensure model generalizability across different demographics and cultural contexts.

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