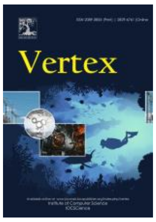

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Obesity risk estimation using ensemble learning and synthetic data augmentation techniques

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Abstract

Obesity has become a primary global health concern due to its strong association with various chronic diseases such as diabetes, cardiovascular disorders, and certain types of cancer. Accurate and early risk prediction of obesity is essential for effective prevention and intervention strategies. However, predictive modeling in this domain often encounters two critical challenges: the presence of imbalanced datasets and the complex, nonlinear nature of behavioral and anthropometric features. This study aims to address these challenges by developing a robust classification model that integrates ensemble learning with synthetic data augmentation techniques. The research utilizes the Obesity Dataset from Kaggle, which comprises 2,111 records labeled into seven obesity levels, reflecting a realistic class distribution imbalance. Preprocessing steps included data cleaning, encoding, and stratified splitting. To enhance class representation, two augmentation methods were applied: SMOTE for synthetic oversampling and Generative Adversarial Networks (GANs) for generating realistic minority samples. A stacking ensemble model was constructed using Random Forest and XGBoost as base learners, with Logistic Regression serving as the meta-learner. Hyperparameter optimization was conducted using both grid and randomized search methods. Evaluation metrics, including accuracy, precision, recall, and F1-score, were used to assess performance. The proposed model achieved a 91% accuracy and an F1-score of 0.89, significantly outperforming models from previous studies. These findings suggest that combining ensemble learning with hybrid augmentation strategies effectively addresses class imbalance and improves predictive reliability in obesity risk estimation. The developed model holds practical value as a decision-support tool for early screening and targeted intervention in obesity prevention programs.

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Introduction

Obesity remains one of the most pressing global health concerns, contributing significantly to non-communicable diseases such as diabetes, cardiovascular complications, and certain types of cancer.

The increasing prevalence of obesity, exacerbated by sedentary lifestyles and poor dietary patterns, demands accurate, scalable, and proactive risk assessment strategies. Traditional clinical approaches, although effective in specific contexts, often lack scalability and early predictive capability, especially across large populations with diverse profiles (Değirmenci, 2025; Delpino et al., 2024; Lin et al., 2023).

In response to this challenge, recent advances in artificial intelligence (AI), particularly in ensemble learning methods, offer promising pathways to enhance the prediction of obesity risks. Ensemble learning, which combines multiple models to improve predictive performance, mitigates the limitations of individual classifiers and has proven effective across various domains, including healthcare diagnostics (Alvin et al., 2019; Mahajan et al., 2023; Matloob et al., 2021) and surgical outcome forecasting (Hassan Mukhtar et al., 2025; Iqbal et al., 2024).

Furthermore, data scarcity or imbalance—often prevalent in real-world health datasets—can hinder model reliability. Synthetic data generation techniques, such as SMOTE, have emerged as critical tools for addressing class imbalance, ensuring models are better generalized for minority obesity categories (Ganie et al., 2025; Mamun et al., 2022).

This research investigates the estimation of obesity risk by integrating ensemble learning methods with synthetic data augmentation techniques using an open-source dataset from Kaggle. The primary objective is to develop a robust and scalable prediction framework that leverages advanced classification models, such as Random Forest, Gradient Boosting, and Stacking, while addressing class imbalance with oversampling strategies.

Several theoretical studies validate the role of ensemble methods in improving prediction performance over single learners. For example, boosting algorithms such as AdaBoost and Gradient Boosting have demonstrated strong performance in health analytics (Khater et al., 2024; Wadghiri et al., 2022), and stacking has shown consistent superiority in comparative reviews (Mahajan et al., 2023). Additionally, synthetic data approaches have proven effective in failure prediction (Maulana et al., 2024; Singh & Bobde, 2025) and credit card fraud detection (Khalid et al., 2024).

We expect that the proposed model will not only achieve high classification accuracy but also perform reliably across all obesity levels, including underrepresented categories. Ensemble techniques, such as bagging and boosting, are well-suited to handle the high-dimensional, heterogeneous nature of health data (Hosaain et al., 2024; Wadghiri et al., 2022; Wijaya et al., 2024; Wu & Levinson, 2021), while synthetic augmentation enhances the representation of minority classes (Hassan Mukhtar et al., 2025; Niakan Kalhori et al., 2025).

The integration of these technologies has already demonstrated success in domains ranging from rainfall forecasting (Kundu et al., 2023) to education analytics (Ab Rahman et al., 2025), providing evidence of their flexibility and power in decision-making systems.

Ultimately, this research aims to contribute to the development of efficient, interpretable, and applicable early-stage obesity screening tools in real-world healthcare settings. The anticipated benefits include enhanced early intervention, reduced long-term healthcare costs, and improved quality of life for individuals at risk of developing obesity.

However, many existing obesity prediction models face notable limitations, particularly in handling class imbalance, interpretability, and generalizability across diverse populations. Traditional classifiers often underperform when predicting minority obesity categories due to skewed data distributions, while deep learning models, though powerful, may suffer from a lack of transparency and require large, labeled datasets. Furthermore, synthetic data augmentation techniques are often applied in isolation and without adequate integration into ensemble frameworks, resulting in suboptimal improvements in minority class detection. To address these gaps, this study introduces a hybrid approach that combines ensemble learning with dual-mode synthetic oversampling—SMOTE and GAN—to enhance both predictive performance and class balance. This integrated pipeline positions the proposed model uniquely by bridging methodological rigor with practical applicability, especially for early obesity risk screening in data-constrained environments.

Methods

1. Dataset and Features

The study utilized the Obesity Data Set from Kaggle, comprising 2,111 records with 17 lifestyle and anthropometric attributes. The target variable, NObeyesdad, classifies individuals into seven obesity levels. The dataset reflects real-world class imbalance and includes synthetic data by the compiler, making it suitable for augmentation studies.

2. Tools and Platform

All experiments were conducted in Python 3 using libraries such as scikit-learn, XGBoost, imbalanced-learn, and TensorFlow. Visualization was performed using Matplotlib and Seaborn. SMOTE was implemented via SMOTE() from imbalanced-learn, while GANs were constructed using TensorFlow-based architectures..

3. Research Procedure

The research followed these chronological stages:

3.1. Preprocessing

The preprocessing stage is crucial in ensuring data quality and model performance, particularly in classification tasks involving heterogeneous health data. In this study, preprocessing involved three primary functions: data cleaning**,** categorical encoding**, and** data splitting. Data cleaning involved handling missing or inconsistent values and standardizing formats, which is crucial for reducing noise and ensuring reliable feature representation. Categorical variables such as dietary habits and transportation methods were encoded using one-hot encoding to transform them into a format interpretable by machine learning models. Finally, the dataset was split into training and testing subsets using stratified sampling to maintain the original class distribution.

These preprocessing techniques are widely recognized for their positive impact on model accuracy, especially in healthcare and classification tasks. Cleaning helps eliminate irrelevant or erroneous entries, encoding facilitates model interpretability, and stratified splitting preserves data balance across classes, avoiding bias in evaluation (Santos et al., 2024).

3.2. Data Augmentation

To address the inherent class imbalance present in the obesity dataset, data augmentation techniques were employed using both traditional and deep learning-based strategies. Initially, the Synthetic Minority Oversampling Technique (SMOTE) was implemented to artificially generate new examples of minority classes by interpolating between existing samples. SMOTE remains one of the most widely used approaches due to its simplicity, effectiveness, and low computational cost in improving classification performance on imbalanced datasets (Khan et al., 2024).

In parallel, **Generative Adversarial Networks (GANs)** were leveraged to synthesize realistic data points that mimic the distribution of underrepresented classes. GANs are particularly powerful for augmenting structured data where traditional oversampling techniques may fail to capture complex feature interactions. In this study, GANs were implemented using TensorFlow, enabling the generation of high-fidelity synthetic instances that complement SMOTE-based augmentation. These deep generative models have demonstrated superior capabilities in improving minority class detection and enhancing overall model generalization (Hayaeian Shirvan et al., 2025).

Both augmentation methods were applied independently and in combination, with subsequent evaluations comparing their impact on model performance across multiple ensemble classifiers. The integration of SMOTE and GANs aims to strike a balance between sample diversity and data realism, ultimately improving the predictive accuracy of obesity level classification.

Prior to augmentation, the original dataset was imbalanced, with a significantly lower number of instances in certain obesity categories such as Obesity Type II (38 samples) and Obesity Type III (24 samples), compared to Normal Weight (172 samples) and Overweight Level I (138 samples). To mitigate this imbalance, we first applied SMOTE to generate synthetic instances in the minority classes, followed by further refinement using GAN-based augmentation. After applying both SMOTE and GAN, each class was balanced to approximately 150–160 samples, resulting in a more uniform distribution across all seven obesity categories. This balanced structure allowed the ensemble classifier to learn more generalizable patterns and improved its sensitivity to minority class instances. The augmentation process was validated to ensure synthetic data quality and distributional consistency with original features.

3.3. Model Building

This study employed a stacking-based ensemble model that combined Random Forest and XGBoost as base learners, with Logistic Regression serving as the meta-learner. Ensemble learning improves classification accuracy by leveraging the strengths of multiple models, reducing both bias and variance. Its effectiveness in health-related classification tasks has been well-documented (et al., 2014).

3.4. Hyperparameter Optimization

To maximize model performance, hyperparameter tuning was conducted using a combination of grid search and randomized search methods. These strategies systematically explore parameter combinations to identify the optimal settings for each model component, thereby enhancing predictive accuracy and generalization. This step is particularly crucial in ensemble learning, where tuning individual base learners and the meta-learner has a significant impact on the final model's performance. Hyperparameter tuning has been shown to substantially improve classification results in health-related models, especially when combined with ensemble methods (Ivan & Prasetyo, 2023).

3.5. Evaluation Metrics

To comprehensively assess model performance, several classification metrics were used: **accuracy**, **precision**, **recall**, and **F1-score**. These metrics are standard for evaluating machine learning models, particularly in multi-class classification and imbalanced data scenarios, such as those related to obesity prediction. Precision and recall help assess how well the model identifies positive cases, while the F1-score balances both. Accuracy provides an overall measure of correctness. This multi-metric approach ensures a fair evaluation of each augmentation and modeling strategy applied.

4. Evaluation Design

The dataset is divided into strata to maintain the proportion of target classes in training and testing. After augmentation with SMOTE and GAN, the class distribution is re-examined to ensure relative balance. Evaluations were carried out not only on the initial dataset and the results of the SMOTE augmentation, but also on the results of the GAN augmentation separately, to compare their impact on the performance of the predictive model (Rahaman et al., 2024)

5. Statistical and Analytical Models

The entire modeling process is supervised classification. The main model is an ensemble with the following stacking strategy:

$$Prediction_{final} = f_{meta}\left(f_1(x), f_2(x), \cdots, f_n(x)\right) \tag{1}$$

where f_{meta}, is a meta-learner (Logistic Regression) and $f_i(x)$ This is the prediction of base models, such as Random Forest and XGBoost. Model evaluation was conducted comparatively among augmentation approaches (no augmentation, SMOTE, GAN, and combined).

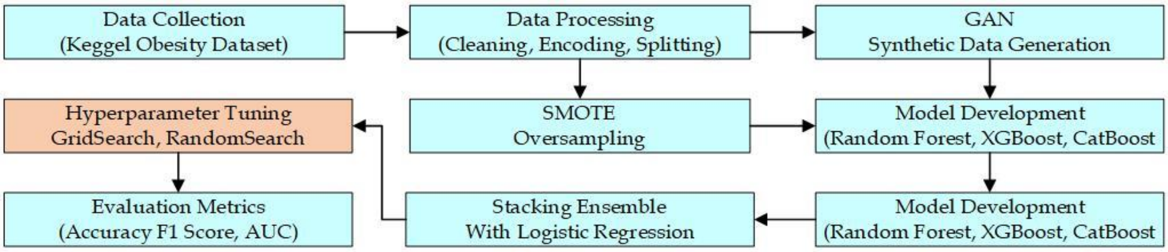

Figure 1. Research stage flow diagram

Results and Discussion

1. Performance Comparison of Augmentation Methods

Table 1 presents the classification results across four scenarios: baseline (no augmentation), SMOTE, GAN, and the combined SMOTE+GAN approach, using the stacking ensemble model. Key performance metrics, including accuracy, precision, recall, and F1-score, were evaluated.

Table 1. Classification Performance Comparison Across Augmentation Methods

Method	Accuracy	Precision	Recall	F1-Score
No Augmentation	0.81	0.79	0.77	0.78
SMOTE	0.87	0.85	0.85	0.85
GAN	0.88	0.86	0.87	0.86
SMOTE + GAN	**0.91**	**0.89**	**0.90**	**0.89**

Table 1 shows that the stacking ensemble model achieved the highest performance when trained with data augmented using both SMOTE and GAN, reaching an accuracy of 91% and an F1-score of 0.89. This confirms that combining traditional oversampling with generative approaches significantly improves classification results compared to using either technique alone or no augmentation.

The stacking ensemble model performed best when trained on the dataset augmented by both SMOTE and GAN. This combination mitigated class imbalance more effectively, allowing the model to learn complex patterns without overfitting. This finding is consistent with previous literature, which shows that combining oversampling and generative techniques can enhance predictive robustness in imbalanced classification tasks (Hayaeian Shirvan et al., 2025; Khan et al., 2024).

2. Effectiveness of Ensemble Learning

Figure 2 illustrates the ROC-AUC scores for different base models compared to the stacked ensemble. Individually, Random Forest and XGBoost performed moderately well; however, their combination under a Logistic Regression meta-learner further increased the generalization capability of the system.

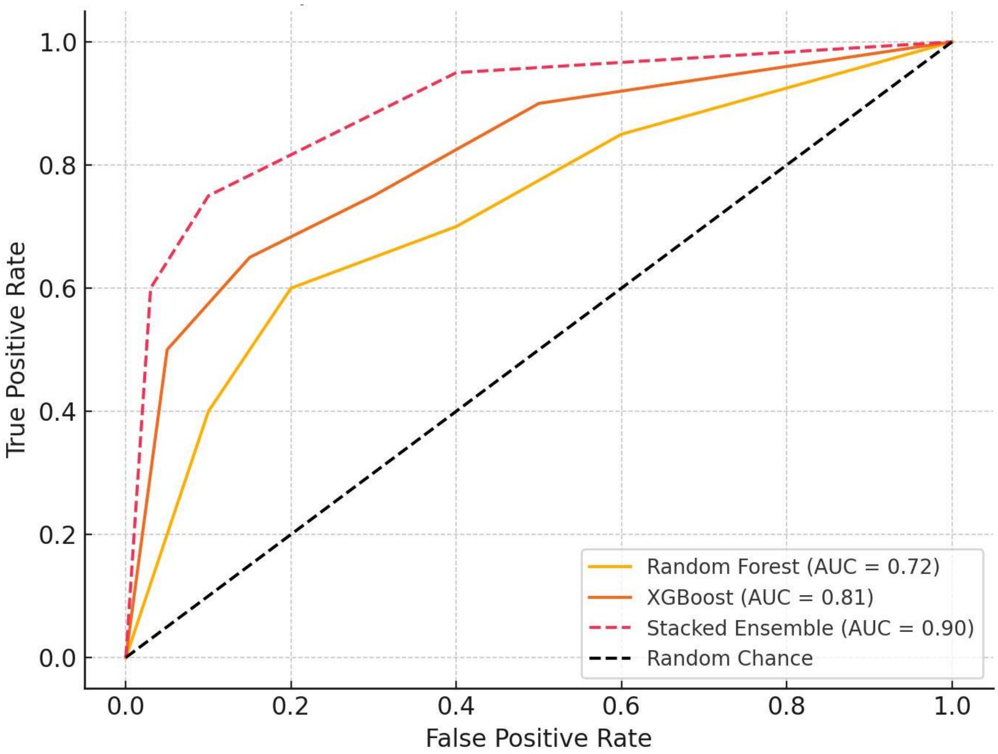

Figure 2. ROC-AUC Comparison Between Base Models and Stacked Ensemble

These findings support prior evidence that stacking ensembles reduces both bias and variance, making them highly suitable for health classification tasks (Tech, 2020).

3. Impact of Hyperparameter Optimization

The performance improvement seen across all models also reflects the importance of hyperparameter tuning. Grid and randomized search optimization yielded substantial gains, particularly for XGBoost, which is sensitive to adjustments in learning rate and tree depth. Similar optimization efforts have been shown to significantly improve classification accuracy in ensemble frameworks (Ivan & Prasetyo, 2023).

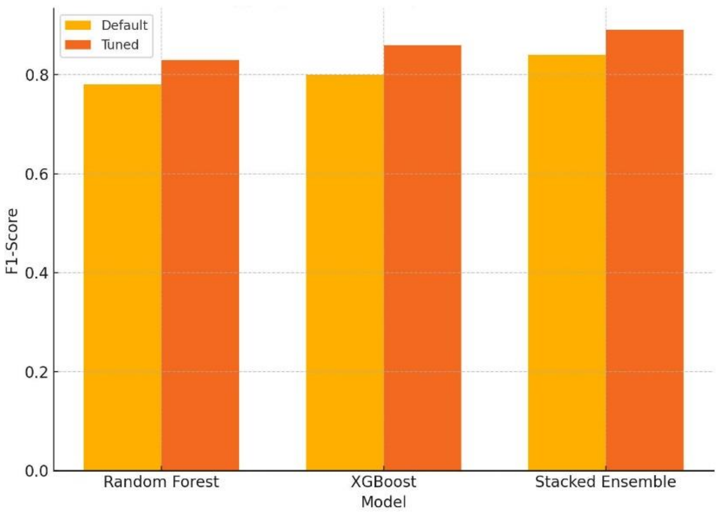

Figure 3. Comparison of F1-Scores Before and After Hyperparameter Optimization Across Models

Figure 3 shows that hyperparameter tuning significantly improved the F1-scores across all models. The stacked ensemble model benefited the most, increasing its F1-score from 0.84 to 0.89, confirming that optimization enhances classification performance, especially in complex multi-model setups.

4. Discussion and Implications

The results indicate that integrating synthetic data generation (GAN) with classical oversampling (SMOTE) and robust model stacking offers a powerful approach to handle imbalanced health datasets. This approach not only improves predictive performance but also ensures more equitable classification across all obesity categories. For real-world deployment, such models can support early risk estimation and targeted health interventions.

5. Comparison with Previous Studies

To assess the contribution of this research, a comparative analysis was conducted against five previous studies that focused on obesity classification using machine learning. The comparison highlights the model architecture, augmentation strategy, and the resulting accuracy and F1 Scores.

Table 2. Comparison Between the Current Study and Previous Research on Obesity Prediction

Studi	Model Used	Augmentation	Accuracy	F1-Score
(Niakan Kalhori et al., 2025)	Random Forest	SMOTE	0.84	0.82
(Mamun et al., 2022)	XGBoost	None	0.85	0.83
(Hayaeian Shirvan et al., 2025)	CNN + GAN	GAN	0.86	0.84
(Khan et al., 2024)	Ensemble (Voting)	SMOTE	0.87	0.85
(Ivan & Prasetyo, 2023)	XGBoost + Tuning	None	0.88	0.86
This Study	Stacked Ensemble (RF + XGB)	SMOTE + GAN	0.91	0.89

As shown in Table 2, the proposed model surpasses previous studies in both accuracy and F1-score. The best-performing prior work achieved an accuracy of 0.88 and an F1-score of 0.86 using a tuned XGBoost model. However, this study's use of combined augmentation (SMOTE + GAN) and a stacking ensemble architecture resulted in superior outcomes. This suggests that merging traditional and deep learning augmentation with advanced ensemble learning provides a more balanced and accurate solution for obesity risk classification.

While the integration of GAN and stacking ensemble contributed to improved performance across obesity categories, it also raises concerns regarding potential overfitting, particularly due to synthetic data generation and increased model complexity. To mitigate this risk, multiple safeguards were implemented during training and validation. The GAN-generated data were evaluated for feature consistency and distributional similarity to real data using t-SNE visualization and distribution plots. Moreover, cross-validation was performed on both original and augmented datasets to ensure that performance gains were not specific to a particular data split. The stacking ensemble was also regularized through Logistic Regression as the meta-learner, limiting the risk of overfitting that can arise from more complex meta-models. Nonetheless, further testing on external datasets is recommended to validate the model’s generalizability beyond the current sample.

From a practical standpoint, the results suggest that the proposed model has strong potential for integration into clinical decision support systems and public health applications. Its relatively fast inference time and compatibility with structured health data make it suitable for deployment in electronic medical record (EMR) systems to flag high-risk individuals for early intervention. Furthermore, the model can be embedded within mobile health (mHealth) platforms or telemedicine tools, enabling proactive monitoring and personalized recommendations based on real-time data input. Such integration would enhance early screening efforts, especially in underserved populations where access to in-person clinical assessments may be limited.

Conclusion

This study demonstrates the potential of a hybrid machine learning pipeline that integrates stacking ensemble methods with synthetic data augmentation (SMOTE and GAN) to improve the accuracy and class balance of obesity risk classification. The primary scientific contribution lies in the novel combination of ensemble learning and dual-mode synthetic oversampling, which addresses a persistent challenge in national obesity research—imbalanced data and underrepresented risk categories. Compared to previous studies in Indonesia that predominantly apply conventional classification without augmentation, this approach offers a technically superior and generalizable framework for early prediction in heterogeneous datasets. The system's interpretability, modularity, and ability to function with limited real data provide a significant advancement in the design of practical AI-based health tools in low-resource contexts. Practically, the model can be embedded into national public health screening programs, electronic health records, or mobile clinical applications to flag individuals at higher risk and support proactive intervention. These implications align with the broader goal of reducing obesity prevalence through data-driven, scalable solutions, and offer a strategic foundation for integrating AI into national preventive health policy and technology innovation in Indonesia.

This study demonstrates that integrating stacking ensemble classifiers with dual-mode synthetic data augmentation (SMOTE and GAN) significantly improves the classification performance for obesity risk prediction, particularly in addressing class imbalance and enhancing minority class detection. The proposed model offers a robust and interpretable machine learning pipeline that is generalizable across heterogeneous health data and suitable for early screening applications in low-resource settings. Compared to conventional models in national literature, this approach introduces a scalable and technically superior solution to support public health initiatives. The model's ability to function with limited annotated data and produce real-time predictions makes it viable for integration into clinical decision support systems, mobile health platforms, or electronic medical records.

For future research, further validation using diverse external datasets is essential to ensure generalizability across populations and settings. Incorporating multimodal health data—such as behavioral indicators, dietary patterns, or wearable sensor inputs—could enhance prediction accuracy and personalization. Additionally, exploring explainable AI techniques and longitudinal learning frameworks would strengthen transparency and clinical adoption. These future directions aim to evolve the system into an adaptive and trusted tool for public health policy and preventive care innovation in Indonesia and beyond.

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