

Conference abstract

Machine Learning Driven Prediction of Weight-Loss Outcomes in Clinical Weight Management Program

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INTRODUCTION

Clinical weight management programs offer multiple meal plans, yet patient responses to these interventions are highly variable. Personalized approaches that align individual characteristics with optimal dietary strategies may improve weight loss outcomes. Electronic medical record (EMR) data provide a rich source of longitudinal information to support predictive modeling in real-world clinical settings.

METHODS

We analyzed EMR data from 12,267 adult patients enrolled in the Henry Ford Medical Group (HFMG) clinical weight management program. Baseline characteristics included demographics, body mass index (BMI), starting weight, and cardiometabolic risk factors. Participants followed structured meal plans, with serial weight measurements recorded during follow-up. A control group of approximately 6,000 patients who were referred to the program but not enrolled was used for comparison. Supervised machine learning models, including logistic regression, random forests, gradient boosting, and extreme gradient boosting, were developed to predict clinically significant weight loss outcomes, defined as achieving $\geq 5\%$ of total body weight loss overall and at 6 months. Models were trained using a 70/30 train-test split and evaluated using accuracy, sensitivity, and specificity.

RESULTS

Across multiple modeling approaches, ensemble methods demonstrated superior predictive performance compared with traditional models. For predicting $\geq 5\%$ weight loss overall, optimized random forest models achieved test-set accuracies of approximately 69–71%, with high sensitivity for identifying individuals likely to achieve clinically meaningful weight loss. In the subgroup of patients achieving $\geq 5\%$ weight loss at 6 months, model performance remained consistent, with test-set accuracies ranging from 65–67% across ensemble approaches. Gradient boosting models provided balanced sensitivity and specificity, whereas highly sensitive models showed reduced specificity, underscoring the trade-off between identifying responders and minimizing false positives.

CONCLUSIONS

Machine learning approaches applied to real-world EMR data can moderately predict clinically meaningful weight loss in structured weight management programs. These models show promise for guiding personalized meal plan selection based on individual patient characteristics. Future work will focus on external validation, incorporation of behavioral and adherence data, and evaluation of algorithm-guided interventions in prospective clinical trials.



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