## Predicting Diabetes Risk Using Demographics and Health Behaviors: A Support Vector Machine Approach

Exploring how lifestyle and socioeconomic factors shape diabetes risk through machine learning models

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#### Introduction

Diabetes is a major chronic disease influenced by health behaviors and demographics. Machine learning offers tools to predict disease risk, potentially informing prevention efforts. In this study, we use Support Vector Machines (SVMs) to classify individuals diabetes status based on lifestyle factors and demographic information.

## Methodology

- Data Preparation:
  - Selected 10 demographic and health behavior features from the 2022 NHIS survey dataset.
  - Missing and invalid entries were removed.
- Feature Scaling:
  - Applied StandardScaler to normalize predictors.
- Class Balancing:
  - Used SMOTE (Synthetic Minority Oversampling Technique) to balance diabetic and non-diabetic cases in the training set.
- Model Training:
  - Linear SVM (linear kernel)
  - RBF SVM (Radial Basis Function kernel)
  - Polynomial SVM (polynomial kernel)
- Hyperparameter Tuning:
  - Performed GridSearchCV with 5-fold crossvalidation to optimize:
  - C (penalty parameter)
  - Gamma (for RBF kernel)
  - Degree (for polynomial kernel)
- Model Evaluation:
  - Accuracy
  - Recall
  - ROC Curve Analysis

## Technical Background

Support Vector Machines (SVMs) are classification models that find the hyperplane maximizing separation between classes. When data is non-linearly separable, kernel methods (linear, RBF, polynomial) map inputs into higher dimensions.

The SVM optimization problem is:

$$egin{aligned} \min_w \left(rac{1}{2}\|w\|^2 + C\sum \xi_i
ight) \ ext{where} \quad y_i(w\cdot x_i + b) \geq 1 - \xi_i, \ \xi_i \geq 0 \end{aligned}$$

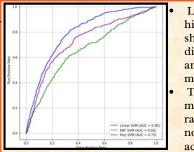
Key hyperparameters include:

- C: Tradeoff between margin size and misclassification penalty
- Gamma: Defines RBF kernel flexibility
- Degree: Controls complexity in polynomial kernels

#### Results

Model	Accuracy	Recall	Fi Score	ROC-AUC
Linear SVM	~68.6%	~79%	~34%	~0.80
Polynomial SVM	~68.6%	~67%	~30%	~0.73
Radial SVM	~82.4%	~27%	~23%	~0.66

- Highest Accuracy: Radial SVM (~82.4%), but low recall for diabetic cases.
- Best Recall for Diabetics: Linear SVM (~79%)
   critical for healthcare prediction.
- Best Overall Discrimination: Linear SVM had highest ROC-AUC (~0.80).

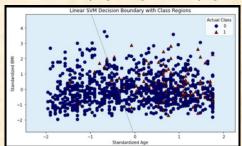


Linear SVM has the highest AUC (~0.80), showing the best discrimination among tuned models.

This indicates it was more effective at ranking diabetic and non-diabetic cases across all thresholds.

#### Discussion

SVM decision boundary separating diabetics by Age and BMI.



The plot shows that age and BMI are the strongest predictors of diabetes in the Linear SVM model. This indicates that older individuals and those with higher body weight are more likely to be at risk. Policy makers should focus on early screening and

# obesity management to help reduce diabetes cases. Conclusion

preventive programs targeting aging populations and

All three SVM models indicate that demographic and lifestyle factors such as age and BMI play a key role in predicting diabetes risk. Although model recall for diabetic cases was not high in all models, these features remain strong signals for prevention. Public health initiatives should emphasize weight control and age-based health interventions to lower diabetes prevalence.

#### Citation

Lynn A. Blewett, Julia A. Rivera Drew, Miriam L. King, Kari C.W. Williams, Daniel Backman, Annie Chen, and Stephanie Richards. IPUMS Health Surveys: National Health Interview Survey, Version 7.4 [dataset]. Minneapolis, MN: IPUMS, 2024