

Type 2 Diabetes



Leveraging BRFSS Survey Data to Predict Diabetes With Known Risk Factors

Course: Data Mining Visualization

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Problem Statement

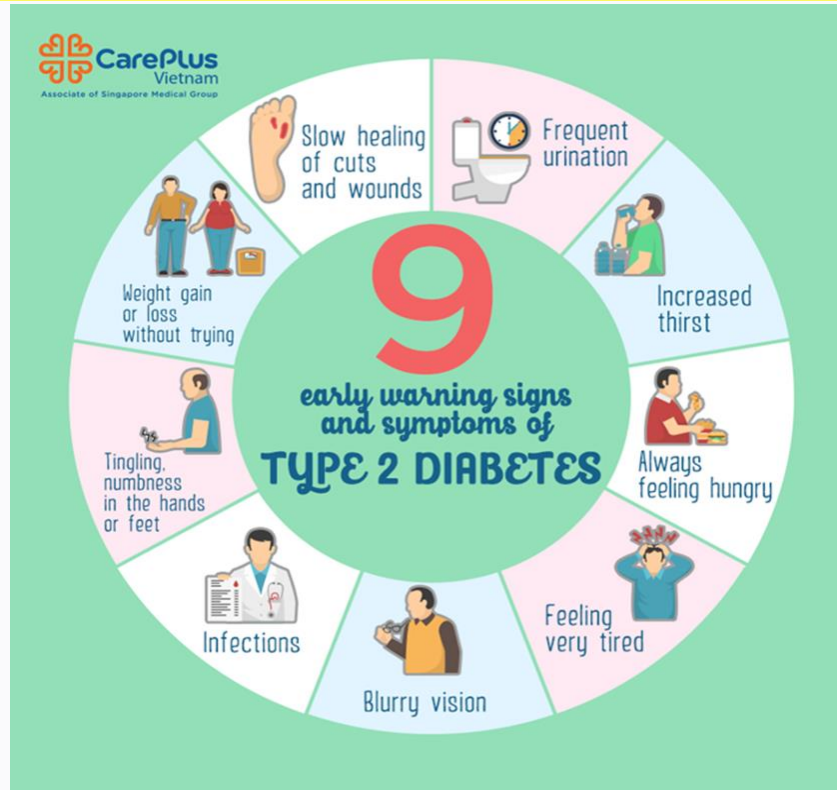
WHAT IS TYPE 2 DIABETES?



Introduction

- Diabetes is a chronic disease that affects millions of people in the US, leading to serious complications that can reduce life expectancy.
- We, as healthcare professionals, are interested in analyzing the risk factors of diabetes to help prevent its onset.
- There are two types of diabetes: Type I and Type II, with Type II being the most common form.
- Our aim is to identify the risk variables in the provided dataset that are most effective in predicting risk for developing Type 2 Diabetes.

Symptoms of the disease



Behavioral Risk Factor Surveillance System



● United States of America

The Behavioral Risk Factor Surveillance System (BRFSS) is the nation's premier system of health-related telephone surveys that collect state data about U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. Established in 1984 with 15 states, BRFSS now collects data in all 50 states as well as the District of Columbia and three U.S. territories. BRFSS completes more than 400,000 adult interviews each year, making it the largest continuously conducted health survey system in the world

Description of Data

**441,455 individuals and has
330 features**

Source: Kaggle using dataset for the year 2015

**253,680 survey responses with
22 feature variables**

Source: We will be using diabetes_012_health_indicators_BRFSS2015.csv
dataset

Target Variable: **(Diabetes_012) with 3 classes**



The data represented in the dataset is records from the
telephonic survey which was collected annually by the CDC.

Source: Kaggle

Diabetes_012 Dataset

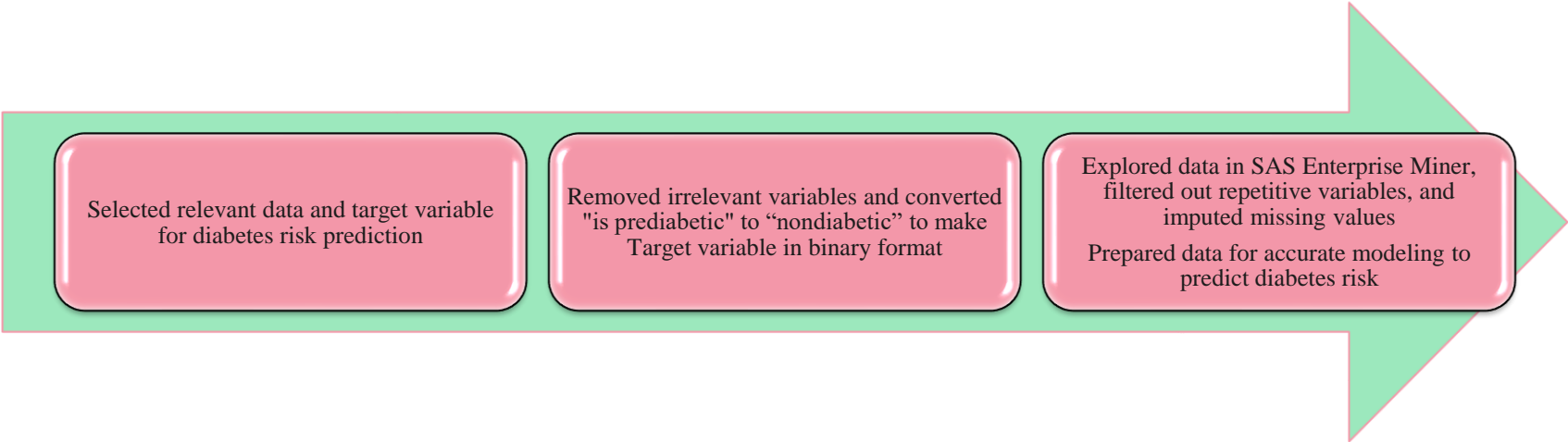


- Diabetes_012 is the target variable in the dataset.
- It has 3 classes: 0 is for no diabetes or only during pregnancy, 1 is for prediabetes, and 2 is for diabetes.

Diabetes_012	Frequency	Percent
Has no diabetes or only during pregnancy	8218	83.94%
Has diabetes	1606	16.06%
Is prediabetic	176	1.76%

Data Exploration Steps

It is the first step of data analysis which is used to explore and visualize data to uncover insights from the start to identify patterns to dig into more.



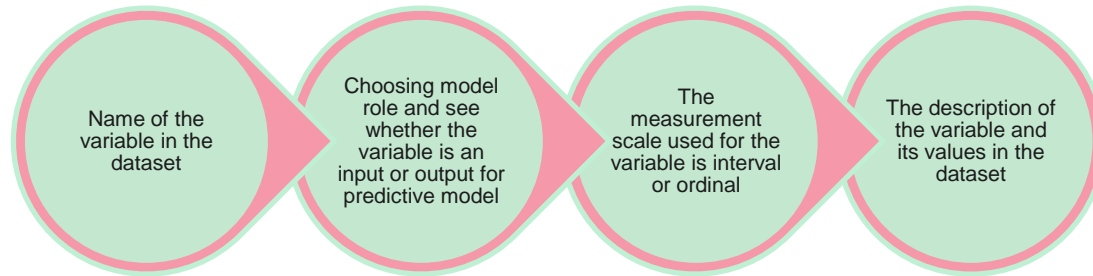
Selected relevant data and target variable
for diabetes risk prediction

Removed irrelevant variables and converted
"is prediabetic" to "nondiabetic" to make
Target variable in binary format

Explored data in SAS Enterprise Miner,
filtered out repetitive variables, and
imputed missing values
Prepared data for accurate modeling to
predict diabetes risk

Data Preprocessing Steps

It is a component of data preparation which describes any type of processing performed on raw data to prepare it for another data processing procedure




Problem , Goal and Constraints

- The BRFSS survey from 2015 provided a dataset of 21 feature variables to predict the risk of developing diabetes.
- The goal is to develop a prediction model that can accurately forecast an individual's risk of developing diabetes.
- However, class imbalance in the dataset, with the majority of replies coming from class 0, presents a major obstacle.

Plan for Data Mining

- The most significant diabetes risk variables were selected using variables graph study and selection approaches.
- SAS Enterprise Miner, a data mining and predictive analytics tool, was used to build the model.
- The plan is broken down into four stages: **data exploration and preprocessing, variable selection, model selection and evaluation.**

Data Preprocessing Result

 Variables - Meta

(none) ☐ not Equal to ☐ Mining ☐ Basic

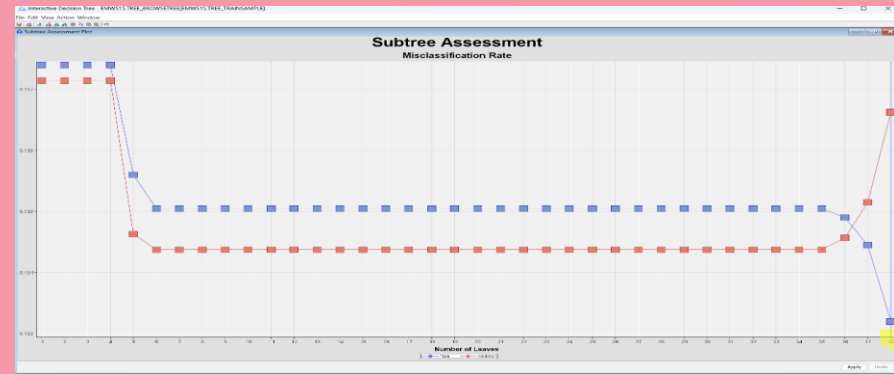
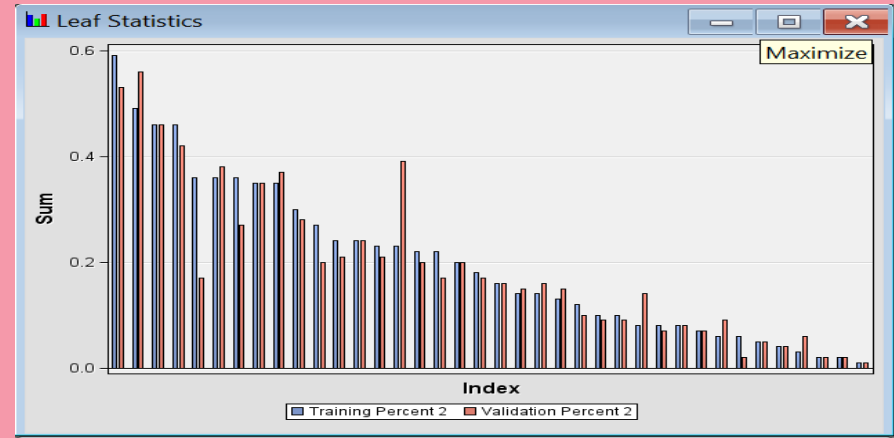
Columns: ☐ Label

Name	Hidden	Hide	Role	New Role	Level	New Level	New Order	New Report
Age	N	Default	Input	Default	Interval	Interval	Default	Default
AnyHealthcare	N	Default	Input	Default	Interval	Binary	Default	Default
BMI	N	Default	Input	Default	Interval	Interval	Default	Default
CholCheck	N	Default	Input	Default	Interval	Binary	Default	Default
Diabetes_012	N	Default	Input	Target	Interval	Binary	Default	Default
DiffWalk	N	Default	Input	Default	Interval	Binary	Default	Default
Education	N	Default	Input	Rejected	Interval	Binary	Default	Default
Fruits	N	Default	Input	Default	Interval	Binary	Default	Default
GenHlth	N	Default	Input	Rejected	Interval	Binary	Default	Default
HeartDiseaseorA	N	Default	Input	Default	Interval	Binary	Default	Default
HighBP	N	Default	Input	Default	Interval	Binary	Default	Default
HighChol	N	Default	Input	Default	Interval	Binary	Default	Default
HvyAlcoholConsu	N	Default	Input	Default	Interval	Binary	Default	Default
Income	N	Default	Input	Default	Interval	Interval	Default	Default
MentHlth	N	Default	Input	Default	Interval	Interval	Default	Default
NoDocbcCost	N	Default	Input	Rejected	Interval	Binary	Default	Default
PhysActivity	N	Default	Input	Default	Interval	Binary	Default	Default
PhysHlth	N	Default	Input	Default	Interval	Interval	Default	Default
Sex	N	Default	Input	Default	Interval	Binary	Default	Default
Smoker	N	Default	Input	Default	Interval	Binary	Default	Default
Stroke	N	Default	Input	Default	Interval	Binary	Default	Default
Veggies	N	Default	Input	Default	Interval	Binary	Default	Default

Model Analysis

Model 1- Maximal Decision Tree

- The maximal tree had 38 leaves, with High BP as the root of the splitting tree.
- Subtree assessment model shows the tree was optimal until 7 leaves, after which it becomes overfitting.
- Misclassification rate for validation was 0.135855.
- However, due to the high level of overfitting, we decided to create another tree model to reduce the noise.
- Further analysis and modeling was conducted to develop an accurate and reliable model for predicting the outcome variable.



Model Analysis

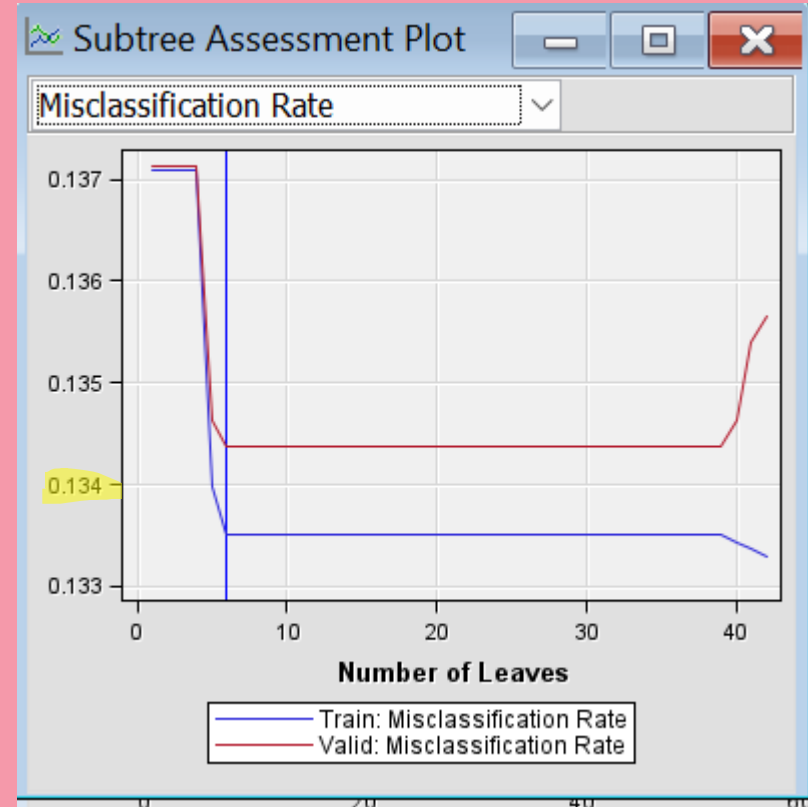
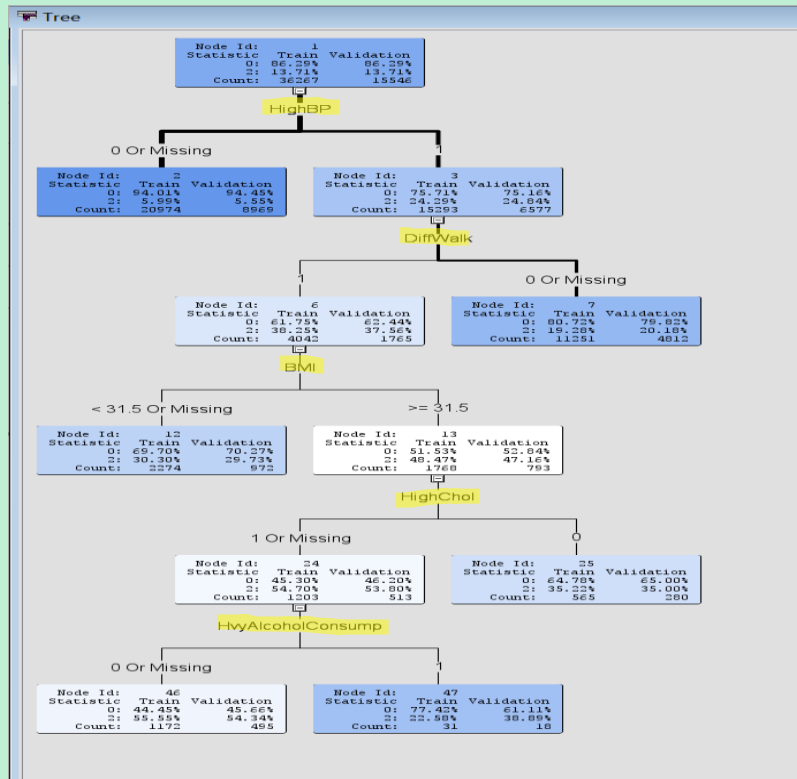
Model 2- Default Decision Tree

- Important Variables: High BP, DiffWalk, BMI, High Chol, HvyAlcohol
- Tree: 6 leaves, High BP as root
- Misclassification validation rate: 0.134375
- Purest leaf:
HighBP=0/missing, Diffwalk=0/missing
- High BP is the main contributing factor in developing Type 2 Diabetes
- Skipped Average Square Error Tree Model due to categorical target variable.

Variable Importance					
Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
HighBP	HighBP	1	1...	1...	1...
DiffWalk	DiffWalk	1	0...	0...	0...
BMI	BMI	1	0...	0...	0...
HighChol	HighChol	1	0...	0...	0...
HvyAlc...	HvyAlc...	1	0...	0...	0...
HeartD...	HeartD...	0	0...	0...	.
MentHlth	MentHlth	0	0...	0...	.
PhysHlth	PhysHlth	0	0...	0...	.
AnvHe...	AnvHe...	0	0...	0...	.
Fruits	Fruits	0	0...	0...	.
Sex	Sex	0	0...	0...	.
Age	Age	0	0...	0...	.
CholC...	CholC...	0	0...	0...	.
Income	Income	0	0...	0...	.
PhysA...	PhysA...	0	0...	0...	.
Stroke	Stroke	0	0...	0...	.
Smoker	Smoker	0	0...	0...	.
Veaqies	Veaqies	0	0...	0...	.

Model Analysis

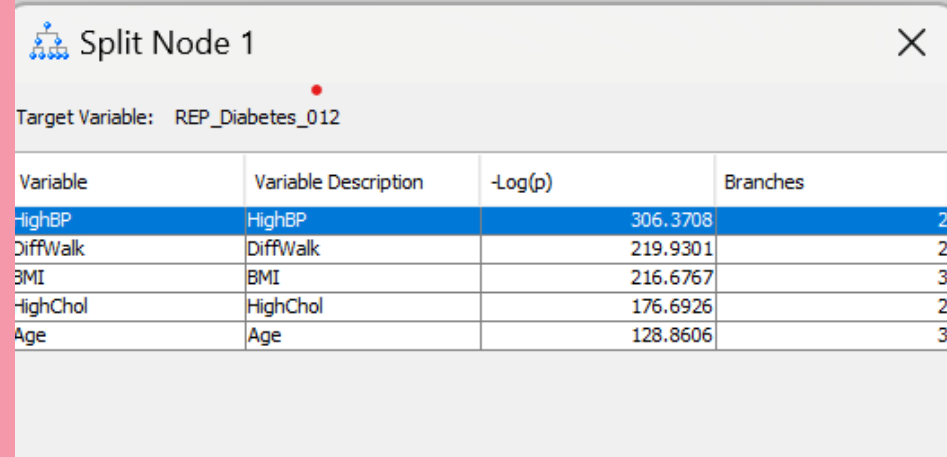
Model 2- Default Decision Tree



Model Analysis

Model 3- Max 3 Decision Tree

- High BP is best for first split
- Competing variables: DiffWalk, BMI, HighChol, Age
- 7 leaves in subtree assessment plot
- Validation misclassification rate: 0.133861
- Purest leaf splitting rule:
High BP=0 or missing High BP=1
- High BP is major factor in predicting type 2 Diabetes



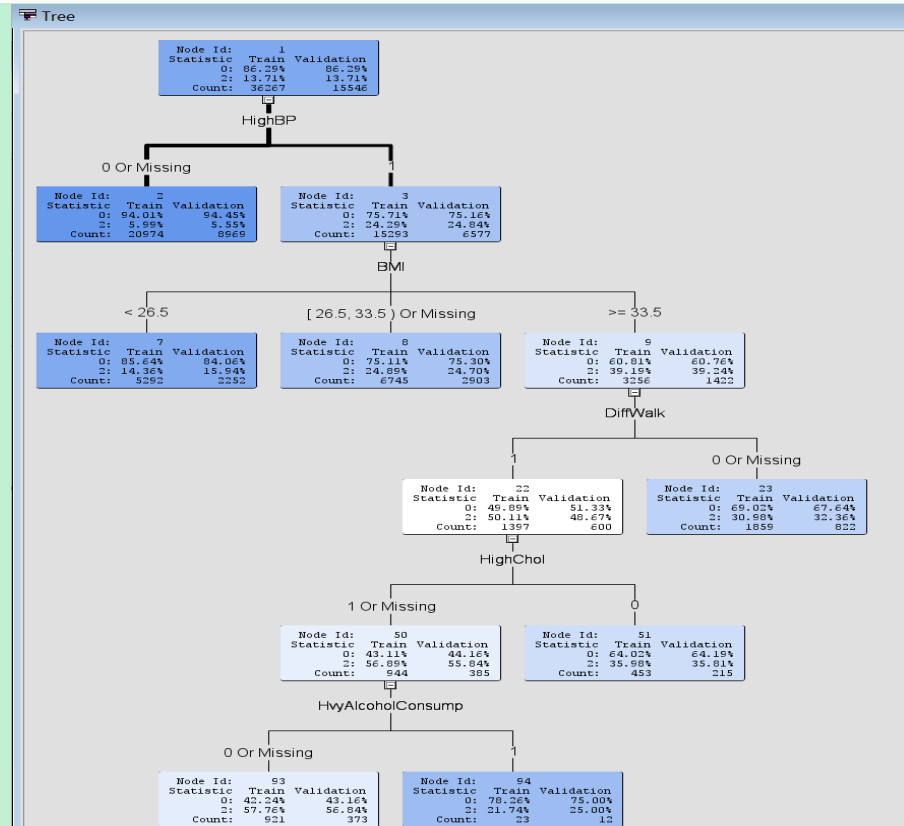
Split Node 1

Target Variable: REP_Diabetes_012

Variable	Variable Description	-Log(p)	Branches
HighBP	HighBP	306.3708	2
DiffWalk	DiffWalk	219.9301	2
BMI	BMI	216.6767	3
HighChol	HighChol	176.6926	2
Age	Age	128.8606	3

Model Analysis

Model 3- Max 3 Decision Tree



Fit Statistics

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation
REP Diabetes 012	Replacement: Diabe...	NOBS	Sum of Frequencies	36267	15546
REP Diabetes 012	Replacement: Diabe...	MISC	Misclassification Rate	0.133151	0.133861
REP Diabetes 012	Replacement: Diabe...	MAX	Maximum Absolute ...	0.940069	0.940069
REP Diabetes 012	Replacement: Diabe...	SSE	Sum of Squared Err...	7648.132	3272.161
REP Diabetes 012	Replacement: Diabe...	ASE	Average Squared Er...	0.105442	0.105241
REP Diabetes 012	Replacement: Diabe...	RASE	Root Average Squar...	0.324718	0.324409
REP Diabetes 012	Replacement: Diabe...	DIV	Divisor for ASE	72534	31092
REP Diabetes 012	Replacement: Diabe...	DFT	Total Degrees of Fr...	36267	.

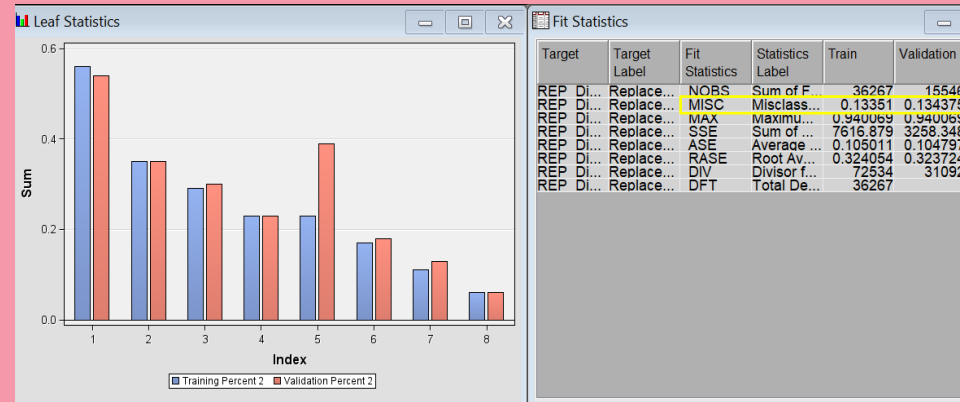
Model Analysis

Model 4-Max 4 Decision Tree

- High BP, DiffWalk, BMI, HighChol, and Age were the selected variables. The tree had 8 leaves with High BP as the root.
- Purest leaf splitting rule: High BP=0 or missing High BP=1 BMI < 23.5.
- Validation misclassification rate: 0.134375.
- Next tree model was not pursued due to higher misclassification rate compared to Max 3 tree.

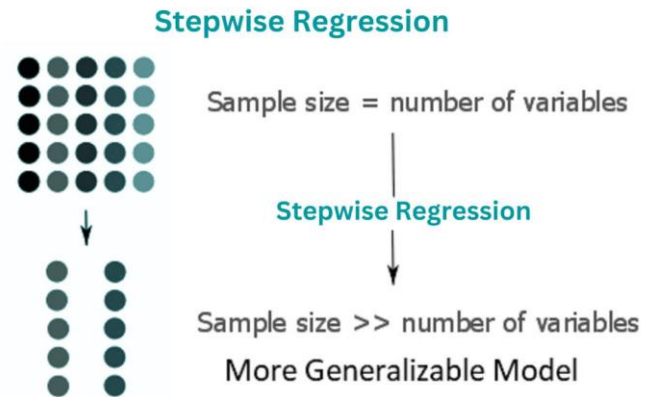
Competing Rules For Node 1

Split Variable	Variable Descri...	-Log(p)	Number of Bran...
HighBP	HighBP	306.3708	2
DiffWalk	DiffWalk	219.9301	2
BMI	BMI	219.6570	4
HighChol	HighChol	176.6926	2
Age	Age	132.9485	4



Model Analysis: Alternative Models

- Two logistic regression models were chosen:
 - (a) Default Regression
 - (b) Stepwise Regression
- Impute node was added to remove missing values and redundant variables.



Model Analysis

Model 5- Default Regression Model

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
Age	1	292.2523	<.0001
AnyHealthcare	1	0.2469	0.6192
BMI	1	832.5025	<.0001
CholCheck	1	41.0074	<.0001
DiffWalk	1	55.1541	<.0001
Fruits	1	1.3601	0.2435
HeartDiseaseorAttack	1	39.0886	<.0001
HighBP	1	454.1584	<.0001
HighChol	1	323.3006	<.0001
HvyAlcoholConsump	1	60.6805	<.0001
Income	1	155.3997	<.0001
MentHlth	1	0.0022	0.9623
PhysActivity	1	15.1811	<.0001
PhysHlth	1	28.4158	<.0001
Sex	1	46.3744	<.0001
Smoker	1	0.0070	0.9334
Stroke	1	11.4499	0.0007
Veggies	1	8.0578	0.0045

Odds Ratio Estimates

Effect	Point Estimate
Age	1.132
AnyHealthcare	0 vs 1 1.042
BMI	1.080
CholCheck	0 vs 1 0.323
DiffWalk	0 vs 1 0.718
Fruits	0 vs 1 1.043
HeartDiseaseorAttack	0 vs 1 0.740
HighBP	0 vs 1 0.437
HighChol	0 vs 1 0.524
HvyAlcoholConsump	0 vs 1 2.145
Income	0.901
MentHlth	1.000
PhysActivity	0 vs 1 1.162
PhysHlth	1.010
Sex	0 vs 1 0.786
Smoker	0 vs 1 0.997
Stroke	0 vs 1 0.801
Veggies	0 vs 1 1.128

•Type 3 Analysis of Effects shows Age, BMI, DiffWalk, HeartDiseaseAttack, HighBP, HighChol, HvyAlcoholConsump, Income, PhysActivity, PhysHlth, and sex are most significant ($p < 0.0001$).

•Odds Ratio shows HvyAlcoholConcsump, PhysActivity, and Age have the most significant effect on the target variable.

•Misclassification rate on validation set was 0.133606, and ASE was 0.099558.

Model 6- Default Regression Model Results

Fit Statistics						
Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
REP Diabetes 012	Replacement: Diabe...	AIC	Akaike's Information...	23541.84		
REP Diabetes 012	Replacement: Diabe...	ASE	Average Squared Er...	0.099418	0.099558	
REP Diabetes 012	Replacement: Diabe...	AVERR	Average Error Funct...	0.324039	0.324814	
REP Diabetes 012	Replacement: Diabe...	DFE	Degrees of Freedo...	36248		
REP Diabetes 012	Replacement: Diabe...	DFM	Model Degrees of F...	19		
REP Diabetes 012	Replacement: Diabe...	DFT	Total Degrees of Fr...	36267		
REP Diabetes 012	Replacement: Diabe...	DIV	Divisor for ASE	72534	31092	
REP Diabetes 012	Replacement: Diabe...	ERR	Error Function	23503.84	10099.1	
REP Diabetes 012	Replacement: Diabe...	FPE	Final Prediction Error	0.099522		
REP Diabetes 012	Replacement: Diabe...	MAX	Maximum Absolute ...	0.991175	0.990802	
REP Diabetes 012	Replacement: Diabe...	MSE	Mean Square Error	0.09947	0.099558	
REP Diabetes 012	Replacement: Diabe...	NOBS	Sum of Frequencies	36267	15546	
REP Diabetes 012	Replacement: Diabe...	NW	Number of Estimate ...	19		
REP Diabetes 012	Replacement: Diabe...	RASE	Root Average Sum ...	0.315306	0.315528	
REP Diabetes 012	Replacement: Diabe...	RFPE	Root Final Predictio...	0.315472		
REP Diabetes 012	Replacement: Diabe...	RMSE	Root Mean Squared...	0.315389	0.315528	
REP Diabetes 012	Replacement: Diabe...	SBC	Schwarz's Bayesian...	23703.31		
REP Diabetes 012	Replacement: Diabe...	SSE	Sum of Squared Err...	7211.195	3095.457	
REP Diabetes 012	Replacement: Diabe...	SUMW	Sum of Case Weigh...	72534	31092	
REP Diabetes 012	Replacement: Diabe...	MISC	Misclassification Rate	0.134751	0.133603	

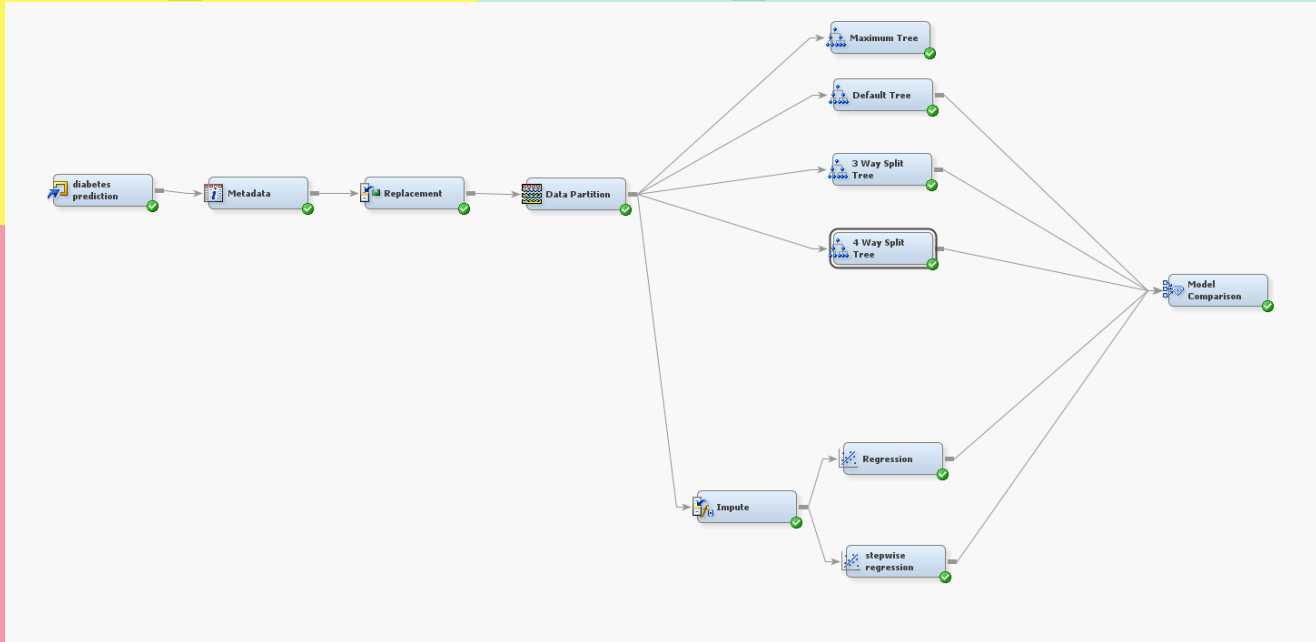
Model Analysis

Model 6- Stepwise Regression Model

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation
REP Diabetes 012	Replacement: Diabe...	AIC	Akaike's Information...	23535.45	
REP Diabetes 012	Replacement: Diabe...	ASE	Average Squared Er...	0.099428	0.099575
REP Diabetes 012	Replacement: Diabe...	AVERR	Average Error Funct...	0.324061	0.324885
REP Diabetes 012	Replacement: Diabe...	DFE	Degrees of Freedo...	36252	
REP Diabetes 012	Replacement: Diabe...	DFM	Model Degrees of F...	15	
REP Diabetes 012	Replacement: Diabe...	DFT	Total Degrees of Fr...	36267	
REP Diabetes 012	Replacement: Diabe...	DIV	Divisor for ASE	72534	31092
REP Diabetes 012	Replacement: Diabe...	ERR	Error Function	23505.45	10101.31
REP Diabetes 012	Replacement: Diabe...	FPE	Final Prediction Error	0.099511	
REP Diabetes 012	Replacement: Diabe...	MAX	Maximum Absolute ...	0.991294	0.990995
REP Diabetes 012	Replacement: Diabe...	MSE	Mean Square Error	0.099469	0.099575
REP Diabetes 012	Replacement: Diabe...	NOBS	Sum of Frequencies	36267	15546
REP Diabetes 012	Replacement: Diabe...	NW	Number of Estimate ...	15	
REP Diabetes 012	Replacement: Diabe...	RASE	Root Average Sum ...	0.315323	0.315555
REP Diabetes 012	Replacement: Diabe...	RFPE	Root Final Predictio...	0.315453	
REP Diabetes 012	Replacement: Diabe...	RMSE	Root Mean Squared...	0.315388	0.315555
REP Diabetes 012	Replacement: Diabe...	SBC	Schwarz's Bayesian...	23662.93	
REP Diabetes 012	Replacement: Diabe...	SSE	Sum of Squared Err...	7211.933	3095.987
REP Diabetes 012	Replacement: Diabe...	SUMW	Sum of Case Weigh...	72534	31092
REP Diabetes 012	Replacement: Diabe...	MISC	Misclassification Rate	0.134861	0.133732

- Variables selected by the algorithm:
Age,
BMI, CholCheck, DiffWalk, HeartDisea
seAttack, HighBP, HighChol, HvyAlco
holConsump, Income, PhysActivity, Ph
ysHlth, Sex, and Veggies
- Misclassification validation rate:
0.133732
- ASE value: 0.099575

Comparison of Experimental results



Model Comparison Node was added, and all the models were assessed.

Comparison of Experimental results by Fit Statistics

- Fit statistics measure how well a model fits a dataset by comparing the predicted outcome to the actual outcome.
- The lower the misclassification rate, the better the model performs.
- The regression model in the study showed slightly lower misclassification rates and Average squared errors compared to the tree models.
- The Default Regression Model had the lowest validation misclassification rate of 0.1336, indicating that it is the best model for predicting an individual's risk of type 2 diabetes.
- The Stepwise Regression was the second-best choice for the model.

Fit Statistics										
Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Misclassification Rate	Train: Sum of Frequencies	Train: Misclassification Rate	Train: Maximum Absolute Error	T
Y	Req	Req	Regres...	REP ...	Replac...	0.1336...	36267	0.1347...	0.9911...	7
	Req2	Req2	stepwi...	REP ...	Replac...	0.1337...	36267	0.1348...	0.9912...	7
	Tree4	Tree4	3 Way ...	REP ...	Replac...	0.1338...	36267	0.1331...	0.9400...	7
	Tree6	Tree6	Gini Tr...	REP ...	Replac...	0.1343...	36267	0.1332...	0.9400...	7
	Tree5	Tree5	4 Way ...	REP ...	Replac...	0.1343...	36267	0.13351	0.9400...	7
	Tree2	Tree2	Default...	REP ...	Replac...	0.1343...	36267	0.13351	0.9400...	7

Conclusions

- **Age, Heavy Alcohol Consumption, and Physical Activity had the greatest effects on the target variable (diabetes_012) according to our best predictive model Logistic Regression**
- The findings emphasize the importance of lifestyle variables and health indicators in determining the likelihood of developing Type 2 Diabetes.
- The research findings can be utilized to improve risk-taking individual prevention strategies and create more precise prediction models.



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Do you have any questions?