Diabetes Prediction

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Summary

In this project we attempt to build a model to predict diabetes disease. We compared a decision tree model and naive bayes model and found the decision tree is stronger in this context. We used f2-score as our scoring function because detecting diabetes is the priority: a false negative could be much worse then a false positive.

In the test dataset: the decision tree model correctly detected 8283 of 10604 positive cases (recall rate is about 78%). This result does come at a fairly significant cost in terms of false positives (precision rate is about 30%) with 19650 false positives. Depending on the actual cost of false positive this may need significant improvement to be a viable screening model.

Introduction

In Canada and the USA approximately 10% of people are living with diabetes. In Canada in 2023 approximately 3.7 million people were living with diabetes and in the USA in 2021 approzimately 38.4 million people were living with diabetes. ("Snapshot of Diabetes in Canada, 2023" (2023)) In the USA it is the 8th leading cause of death. (Rios et al. (2017)) Globally an estimated 44% of people living with diabetes are undiagnosed. (Stafford et al. (2025))

In this project we try to predicted diabetes disease based on common health factors. A reliable model could help to prescreen people and recommend following up with a physician for people who are at risk. Given the large number of people living with undiagnosed diabetes this could potentially have a significant positive impact of world health.

The analysis uses the American CDC Behavioural Risk Factor Surveillance System (BRFSS) 2015 Diabetes Health Indicators dataset (UCI ID 891), containing 253,680 survey responses with 21 health-related features and a binary diabetes outcome (0 = no diabetes/pre-diabetes, 1 = diabetes). (Dane and Teboul (2021))

No missing values were present and all features were already encoded numerically. The target classes is imbalanced (86% non-diabetic, 14% diabetic).

Methods

This analysis was performed in Python 3.11.6 (*Python 3.11.6 Documentation* 2021-2025). Additionally, here is a list of the Python packages used within the analysis with brief explanation:

Package	Version	Use case	Reference
`numpy`	`1.26.4`	General analysis use	*NumPy Documentation* (2008-2022)
`pandas`	`2.1.2`	Data management/processing	team (2020), McKinney (2010)
`pandera`	`0.27.0`	Data valiadion	Bantilan (2020)
`altair`	`5.1.2`	Generating plots	VanderPlas et al. (2018), Satyanarayan et al. (2017)
`scikit-learn`	`1.3.2`	Model creation and evaluation	Pedregosa et al. (2011)
`ucimlrepo`	`0.0.7`	Data extraction	Kelly, Longjohn, and Nottingham (2021)
`deepchecks`	`0.18.1`	Data validation	Chorev et al. (2022)
`click`	`8.3.1`	Script tool	Pallets (2020)
`quarto`	`1.8.26`	Report creation	Allaire et al. (2025)
`tabulate`	`0.9.0`	Table formatting	Astanin (2025)

Modeling Approach

Results

EDA

Data Summary

First, here is a sample of the training data showing the first few entries and last few entries in the dataset in Table 2 and Table 3.

Table 2: First few rows of the training data.

	Unnamed: 0	High	High	CB	BC	Chol	Ch	Sm	Stroke	Heart-Disease-or-Attack	Phys-Activity	Fruits	Veg-	Hvy-Alcohol-Consump	Any-Healthcare	No-Doc-Cost	Gen	Ment	Phys	Diff	Wal	Sex	Age	Education	In-come	di-abetes
0	0	0	1	1	23	0	0	0	1	1	1	0	1	0	1	0	0	0	0	10	6	8	0
1	1	0	0	1	25	0	0	0	1	1	1	0	1	0	3	0	30	0	0	12	6	7	0
2	2	1	1	1	28	0	0	0	1	0	1	0	1	0	2	15	2	0	1	6	5	6	0
3	3	0	0	1	25	0	0	0	0	1	1	0	1	0	2	0	0	0	0	8	5	7	0
4	4	1	0	1	30	1	0	0	1	1	1	0	1	1	4	30	15	0	0	8	4	4	0

Table 3: Last few rows of the training data.

	Unnamed: 0	High	High	CB	BC	Chol	Ch	Sm	Stroke	Heart-Disease-or-Attack	Phys-Activity	Fruits	Veg-	Hvy-Alcohol-Consump	Any-Healthcare	No-Doc-Cost	Gen	Ment	Phys	Diff	Wal	Sex	Age	Education	In-come	di-abetes
0	177571	1	1	1	29	0	0	0	1	1	1	0	1	0	2	0	2	0	0	4	6	5	0
1	177572	0	1	1	22	0	0	0	0	1	1	0	1	0	3	0	0	1	0	13	4	1	0
2	177573	1	1	1	25	1	0	0	1	1	1	0	1	0	2	0	0	0	1	6	5	7	0
3	177574	1	1	1	24	1	0	0	1	1	1	0	1	0	3	2	1	0	0	4	4	8	0
4	177575	1	1	1	31	1	0	0	0	1	1	0	1	0	2	0	2	0	0	8	4	4	0

All features of the dataset are numeric, and further EDA shows there are no null values in the dataset.

Table 4: Description of the training data.

	Unnamed: 0	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	Veggies	HvyAlcoholConsump	AnyHealthcare	NoDocbcCost	GenHlth	MentHlth	PhysHlth	DiffWalk	Sex	Age	Education	Income	diabetes
0	count	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576	177576
1	mean	0.429	0.424	0.963	28.382	0.443	0.041	0.094	0.757	0.634	0.812	0.056	0.951	0.084	0.095	2.511	3.185	3.744	0.168	0.441	8.032	5.050	0.139
2	std	0.495	0.494	0.189	6.608	0.497	0.198	0.292	0.429	0.482	0.391	0.230	0.215	0.278	0.293	7.413	7.507	1.114	0.374	0.496	2.854	2.071	0.346
3	min	0	0	0	12	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0
4	25%	0	0	1	24	0	0	0	1	0	1	0	1	0	2	0	0	0	0	6	4	5	0
5	50%	0	0	1	27	0	0	0	1	1	1	0	1	0	2	0	0	0	0	8	5	7	0
6	75%	1	1	1	31	1	0	0	1	1	1	0	1	0	3	2	3	0	1	10	6	8	0
7	max	1	1	1	98	1	1	1	1	1	1	1	1	1	5	30	30	1	1	13	6	8	1

Table 4 displays a numerical distribution of the dataset. Most features are binary in nature, with the exceptions of To better visualize we then plotted frequency counts of the target labels:

Visualizations

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

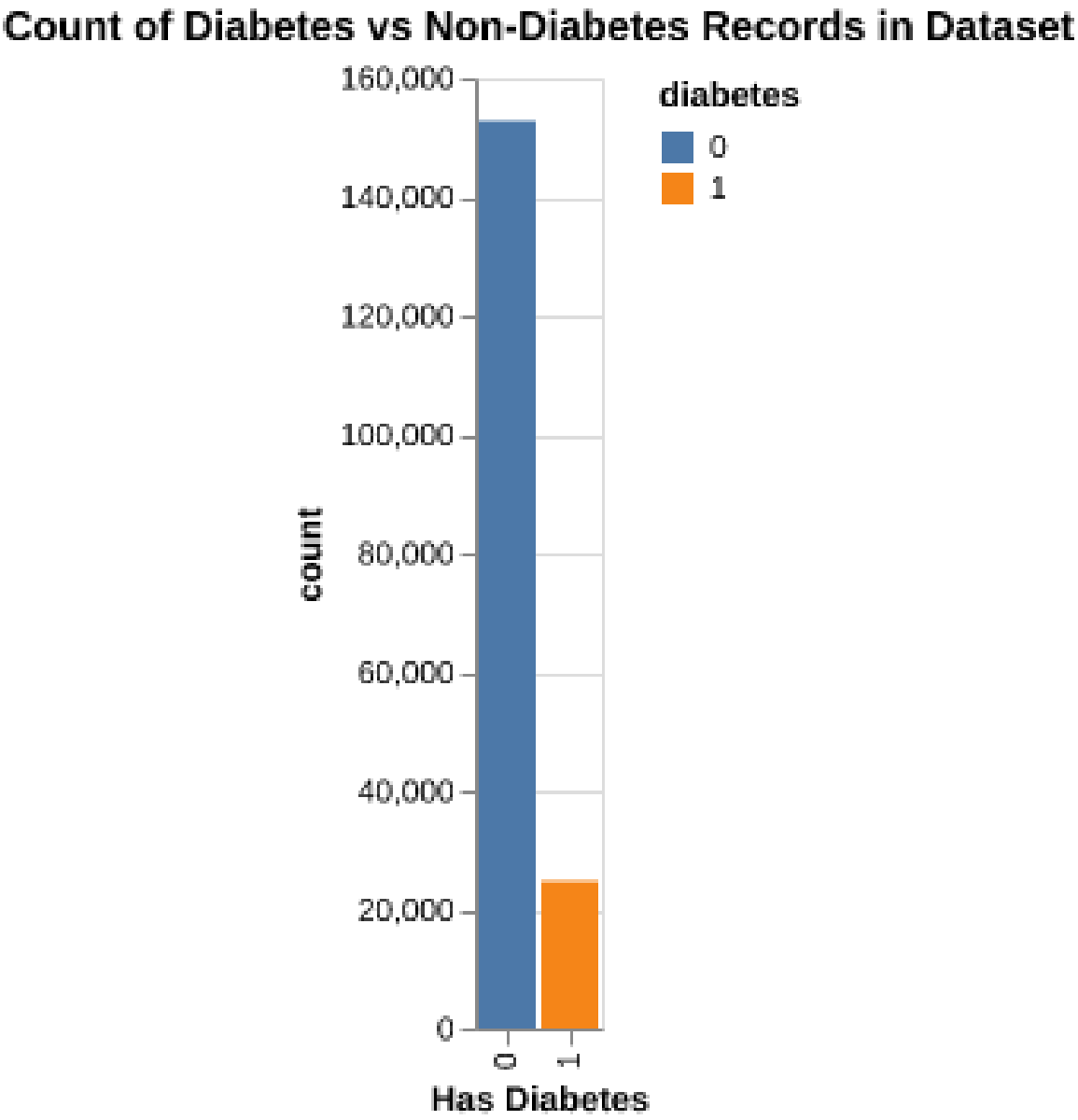

Figure 1: Frequency bar graph of the labels.

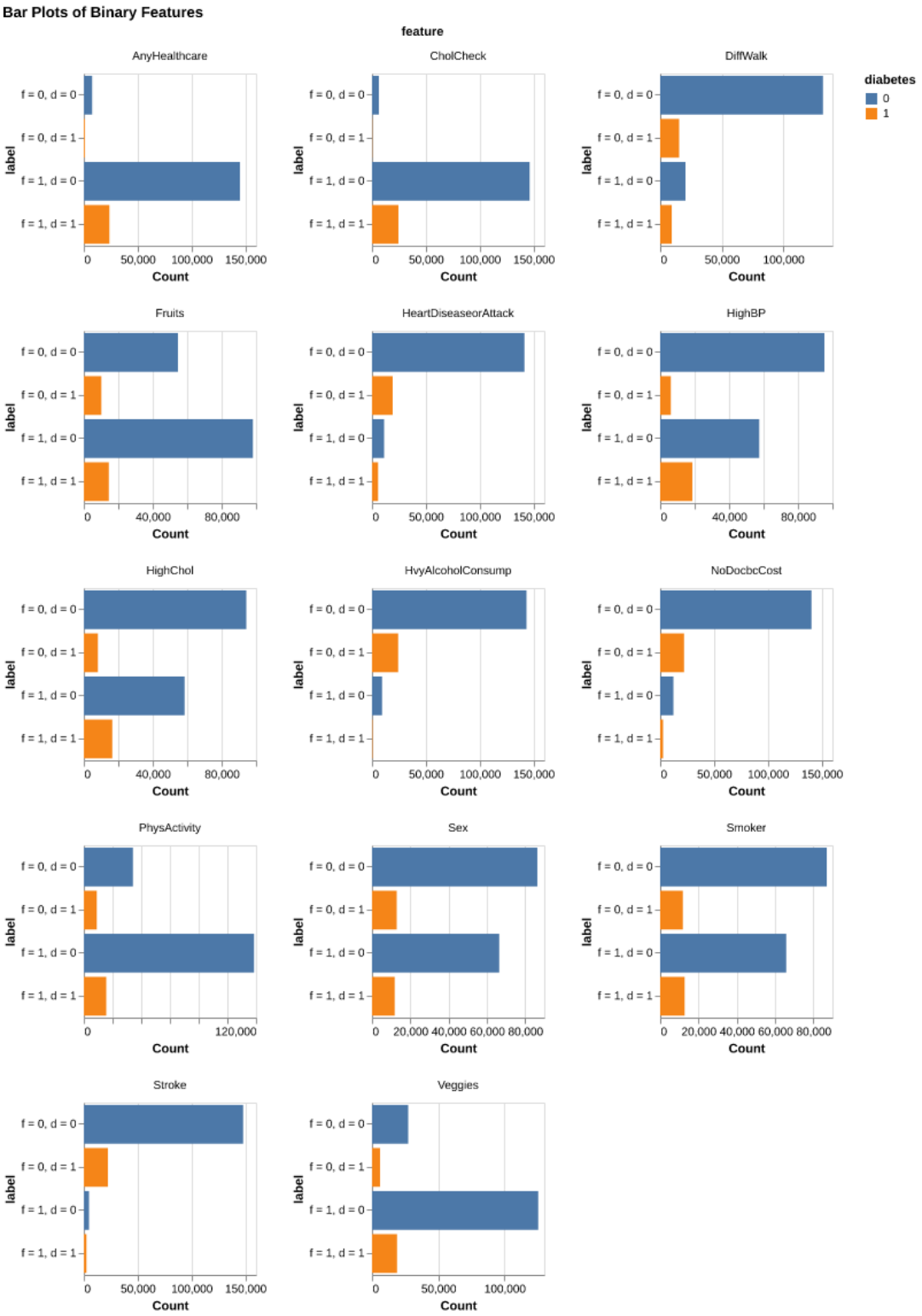

Figure 2: Frequency bar graphs of the binary features.

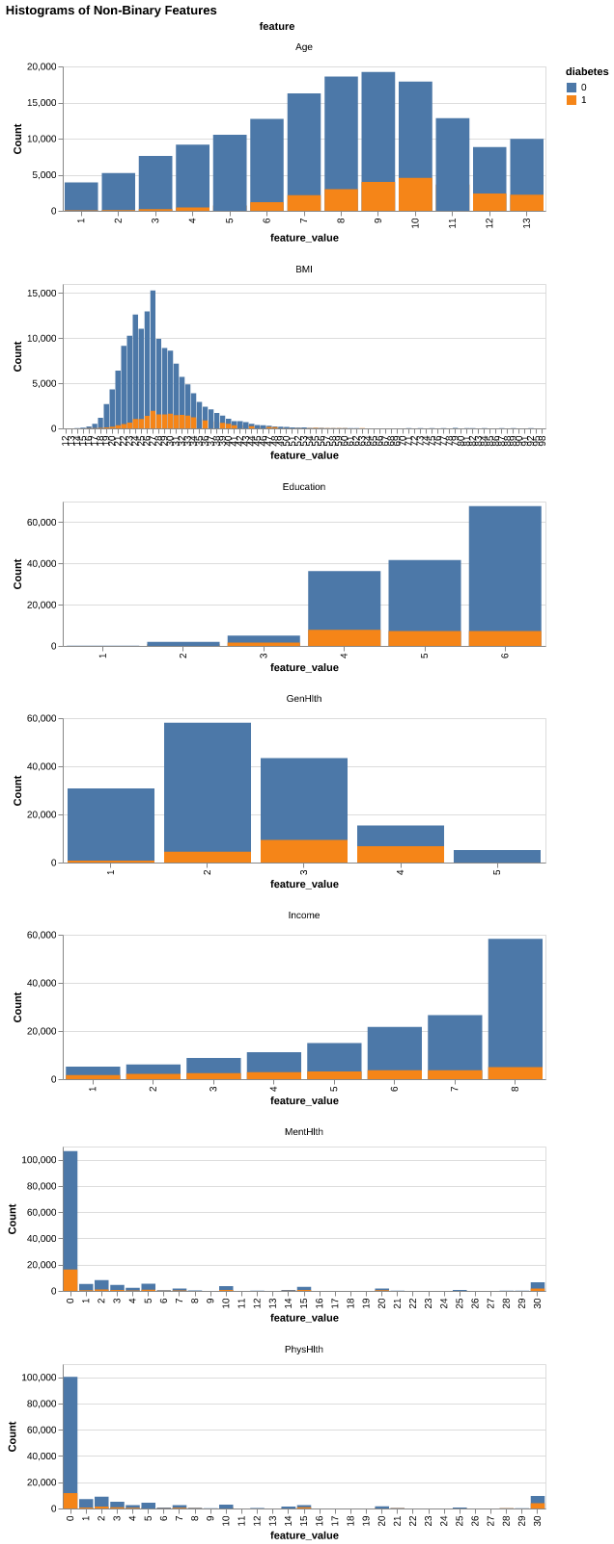

Figure 3: Histograms of the non-binary numeric features.

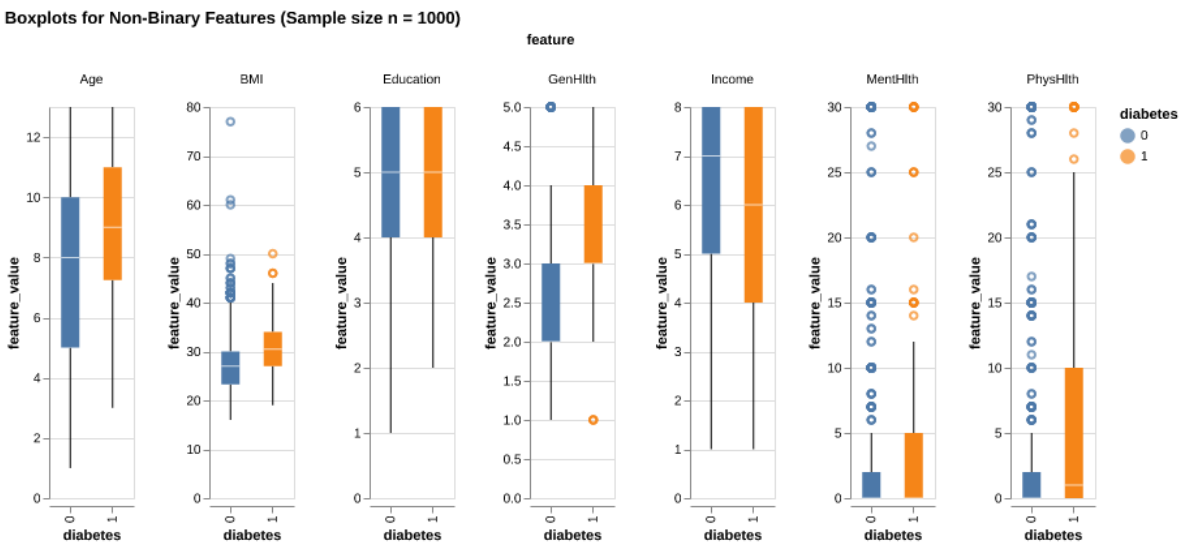

Figure 4: Boxplots of the non-binary numeric features.

Modeling

Classification Analysis

Result Visualizations

Discussion

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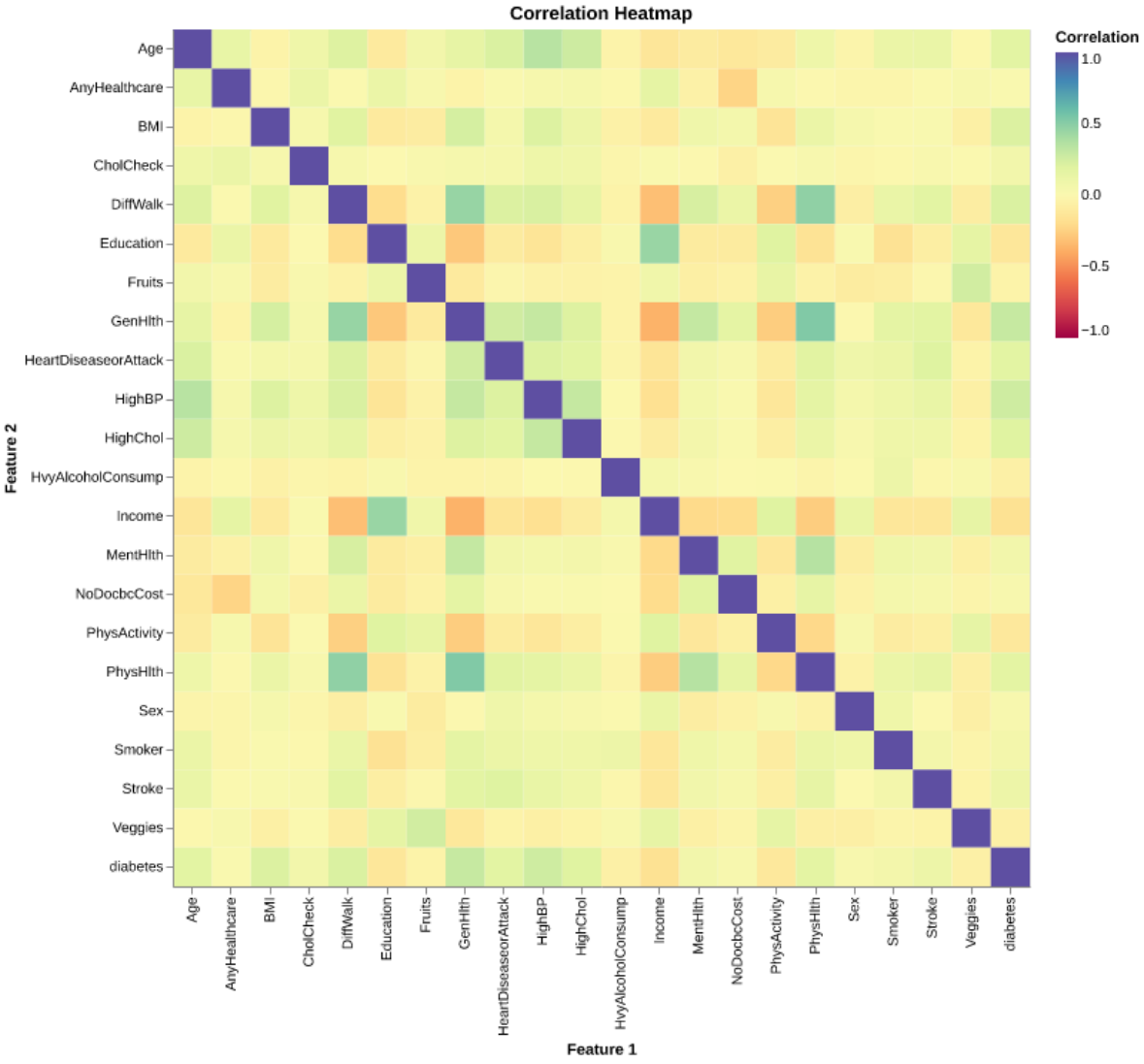

Figure 5: Feature-feature correlation plot of all features.

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