Evaluation of ML Models to Predict Diabetes

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Diabetes Crisis

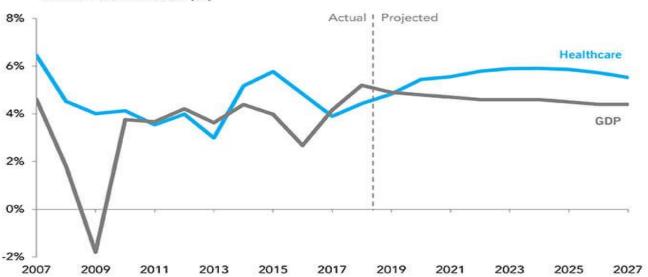
- 37.3 million people in the US have diabetes
- 96 million Americans have prediabetes
- 1 in 4 adults with diabetes don't know they have diabetes
- Can lead to other health issues such as heart disease, kidney disease, nerve damage etc.

Healthcare Spending in America



Healthcare spending is projected to grow faster than the economy over the next decade

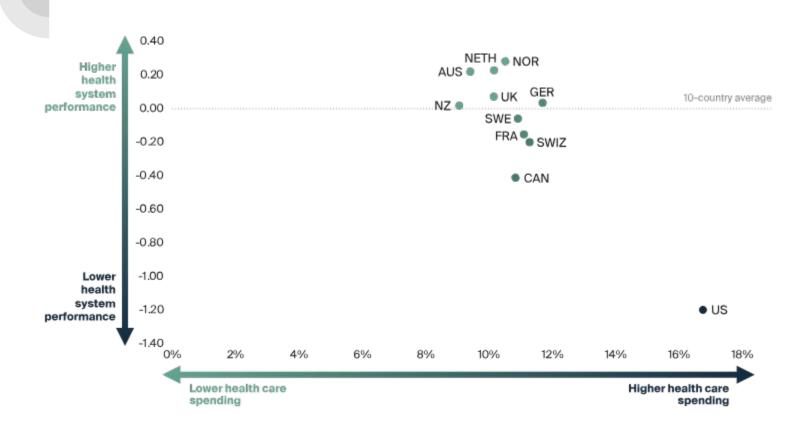
ANNUAL GROWTH RATE (%)



SOURCES: Centers for Medicare and Medicaid Services, National Health Expenditures, February 2019 and Bureau of Economic Analysis, National Income and Product Accounts, April 2019. Compiled by PGPF.

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Spending vs. Performance



Benefits of ML in Healthcare

- Predictive tools allows for early intervention
- Decrease in healthcare costs

National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK)

- Pregnancies
- Glucose
- Blood Pressure
- Skin Thickness
- Insulin
- BMI
- DiabetesPedigreeFunction
- Age
- Outcome (target variable)

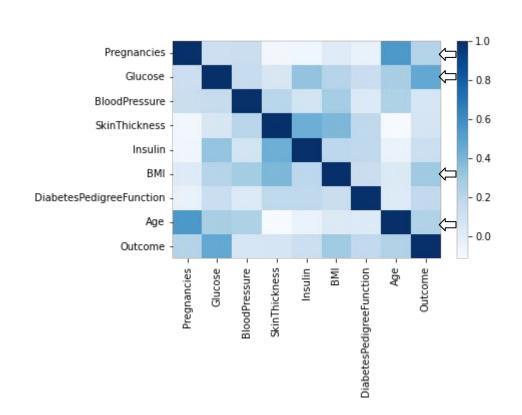
Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age	Outcome
6	148	72	35		33.6	0.627	50	1
8	183	64	0	0	23.3	0.672	32	1
0	137	40	35	168	43.1	2.288	33	1
3	78	50	32	88	31.0	0.248	26	1
2	197	70	45	543	30.5	0.158	53	1
								_
Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age	Outcome
Pregnancies 1	Glucose 85	BloodPressure 66	SkinThickness 29		BMI 26.6	DiabetesPedigreeFunction 0.351	Age 31	Outcome 0
Pregnancies 1				0			- 7	10.000 c c c c c c c c c c c c c c c c c
1	85	66	29	0 94	26.6	0.351	31	0
1	85 89	66 66	29 23	0 94 0	26.6 28.1	0.351 0.167	31 21	0

Statistics - Diabetes vs. No Diabetes

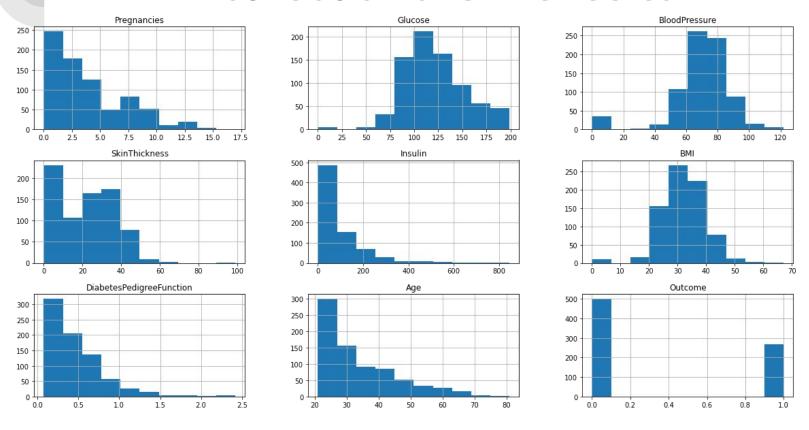
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
count	268.000000	268.000000	268.000000	268.000000	268.000000	268.000000	268.000000	268.000000	268.0
mean	4.865672	141.257463	70.824627	22.164179	100.335821	35.142537	0.550500	37.067164	1.0
std	3.741239	31.939622	21.491812	17.679711	138.689125	7.262967	0.372354	10.968254	0.0
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.088000	21.000000	1.0
25%	1.750000	119.000000	66.000000	0.000000	0.000000	30.800000	0.262500	28.000000	1.0
50%	4.000000	140.000000	74.000000	27.000000	0.000000	34.250000	0.449000	36.000000	1.0
75%	8.000000	167.000000	82.000000	36.000000	167.250000	38.775000	0.728000	44.000000	1.0
max	17.000000	199.000000	114.000000	99.000000	846.000000	67.100000	2.420000	70.000000	1.0
	Pregnancies	Glucose E	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
count	Pregnancies 500.000000	Glucose E 500.0000	BloodPressure 500.000000		Insulin 500.000000	BMI 500.000000	DiabetesPedigreeFunction 500.000000	Age 500.000000	Outcome 500.0
count									
	500.000000	500.0000	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	500.0
mean	500.000000	500.0000 109.9800	500.000000 68.184000	500.000000 19.664000	500.000000	500.000000	500.000000 0.429734	500.000000	500.0
mean std	500.000000 3.298000 3.017185	500.0000 109.9800 26.1412	500.000000 68.184000 18.063075	500.000000 19.664000 14.889947	500.000000 68.792000 98.865289	500.000000 30.304200 7.689855	500.000000 0.429734 0.299085	500.000000 31.190000 11.667655	500.0 0.0 0.0
mean std min	500.000000 3.298000 3.017185 0.000000	500.0000 109.9800 26.1412 0.0000	500.000000 68.184000 18.063075 0.000000	500.000000 19.664000 14.889947 0.000000	500.000000 68.792000 98.865289 0.000000	500.000000 30.304200 7.689855 0.000000	500.000000 0.429734 0.299085 0.078000	500.000000 31.190000 11.667655 21.000000	500.0 0.0 0.0 0.0
mean std min 25%	500.000000 3.298000 3.017185 0.000000 1.000000	500.0000 109.9800 26.1412 0.0000 93.0000	500.000000 68.184000 18.063075 0.000000 62.000000	500.000000 19.664000 14.889947 0.000000 0.000000 21.000000	500.000000 68.792000 98.865289 0.000000 0.000000	500.000000 30.304200 7.689855 0.000000 25.400000	500.000000 0.429734 0.299085 0.078000 0.229750	500.000000 31.190000 11.667655 21.000000 23.000000	500.0 0.0 0.0 0.0 0.0

Correlation to Occurence of Diabetes

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.221898
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.466581
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.065068
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.074752
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0.130548
ВМІ	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0.292695
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0.173844
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0.238356
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1.000000



Distribution of all Variables



Missing Values in the Data

- Glucose
- Blood Pressure
- Skin Thickness
- Insulin
- BMI

Handling Missing Data

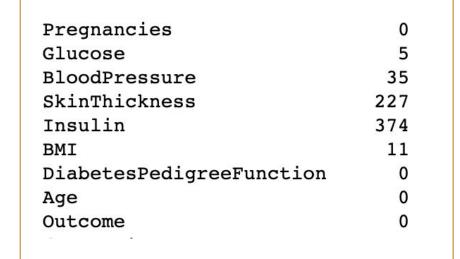
- Three types of missing data
 - Missing completely at random (MCAR) mean, median, mode
 - Missing at random (MAR) multiple imputation, regression imputation
 - Missing not at random (MNAR) pattern substitution, maximum likelihood estimation

Multiple Imputation with Mice Forest Algorithm

• Data missing at random (MAR)

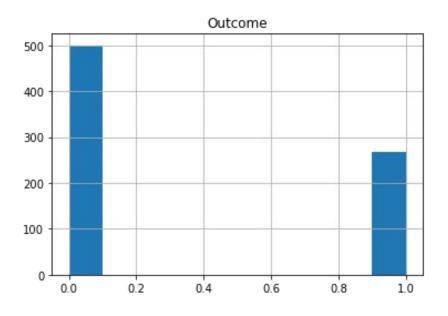
Training a model over multiple iterations to predict the missing values

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	None	33.6	0.627	50	1
1	1	85	66	29	None	26.6	0.351	31	0
2	8	183	64	None	None	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
0	Pregnancies 6	Glucose	BloodPressure 72.0	SkinThickness 35.0	Insulin 130.0	BMI 33.6	DiabetesPedigreeFunction 0.627	Age 50	Outcome 1
0	an section Character and the section of the section	J. 100 100 100 40	10 20 days de 100 March 11 mages de described (no 100 march				•		8
	6	148.0	72.0	35.0	130.0	33.6	0.627	50	1
1	6	148.0 85.0	72.0 66.0	35.0 29.0	130.0 37.0	33.6 26.6	0.627 0.351	50 31	1
1 2	6 1 8	148.0 85.0 183.0	72.0 66.0 64.0	35.0 29.0 21.0	130.0 37.0 120.0	33.6 26.6 23.3 28.1	0.627 0.351 0.672	50 31 32	1 0 1



Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0

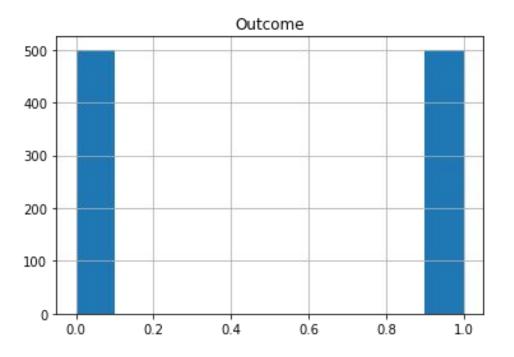
Distribution of the Outcome of Diabetes



Synthetic Minority Oversampling Technique (SMOTE)

• Undersampling vs. Oversampling

Generates new instances for the minority class



Decision Tree Model

• Supervised machine learning model

- Used for classification
 - Occurrence of diabetes vs. no occurrence of diabetes

Random Forest Model

- Supervised machine learning model
- Used for classification
- Combines multiple decision trees to make predictions
- More accurate than decision trees

Accuracy of Models

Decision Tree: 79%

Random Forest: 82%

Evaluation of Machine Learning Models

Confusion matrix

Count of True Positives	Count of False Positives
Count of False Negatives	Count of True Negatives

Evaluation of Decision Tree Model

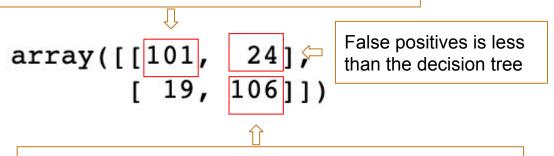
From the test set of the machine learning model, 98 of those points were correctly predicted to have diabetes

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array([[ 98, 27], [ 24, 101]])
```

From the test set of the machine learning model, 101 of those points were correctly predicted to not have diabetes

Evaluation of Random Forest Model

From the test set of the machine learning model, 101 of those points were correctly predicted to have diabetes



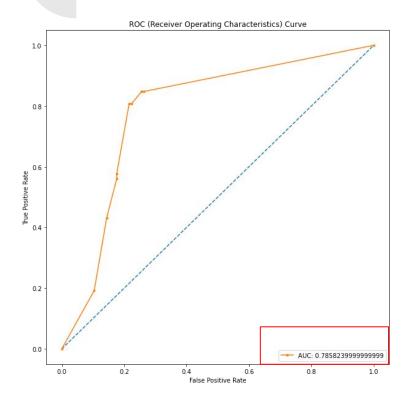
From the test set of the machine learning model, 106 of those points were correctly predicted to not have diabetes

Evaluation of Machine Learning Models

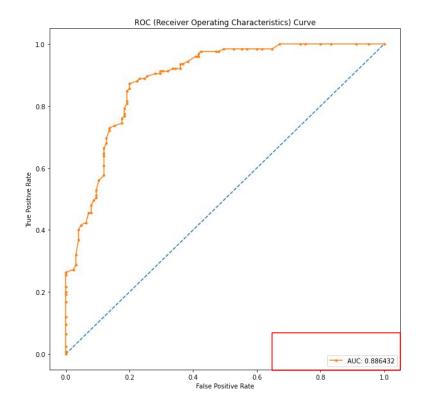
- AUC Curve area under the curve
 - True positive rate vs. false positive rate

Ranges 0-1

Decision Tree



Random Forest



Conclusions

Random forest model performed better

• Using a confusion matrix and AUC curve to evaluate the performance of both models

Great potential for use in healthcare

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