

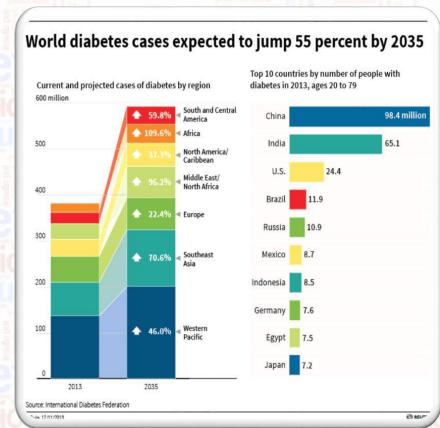
DIABETES DETECTION

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INTRODUCTION

- □ Diabetes is a disease that occurs when your blood glucose, also called blood sugar, is too high. Blood glucose is your main source of energy and comes from the food you eat.
- ☐ Insulin, a hormone made by the pancreas, helps glucose from food get into your cells to be used for energy. Sometimes your body doesn't make enough—or any—insulin or doesn't use insulin well. Glucose then stays in your blood and doesn't reach your cells.
- ☐ Over time, having too much glucose in your blood can cause health problems. Although diabetes has no cure, you can take steps to manage your diabetes and stay healthy.
- ☐ Diabetes is also creator of different kinds of diseases like heart attack, blindness etc.. The normal identifying process is that the patients need to visit a diagnostic center, consult a doctor and sit tight for a day or more to get their reports
- ☐ Cause of diabetes vary depending on the genetic makeup, family history, ethnicity, health etc..
- ☐ Diabetes & pre-diabetes is diagnosed by blood test.



STANDARD PROCESS: CRISP DM

- Crisp DM process is used to better understand the problem and give us better insight of whole process.
- ☐ CRISP DM(Cross Industry Standard Process For Data Mining) has six phases:

1. Business/Research Understanding Phase

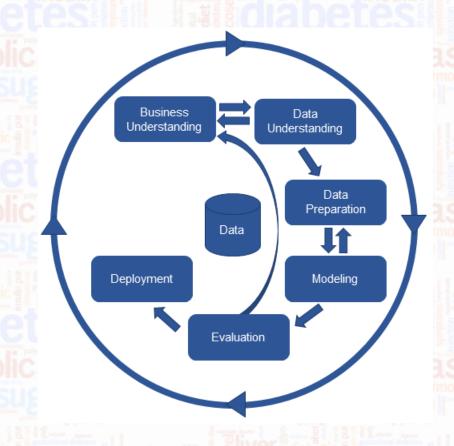
- Determine the business objectives
- To assess the problem and determine data mining goals
- To come up with a strategy to meet goals and objectives

2. Data Understanding Phase

- Collect the data
- Assess and analyse the data

STANDARD PROCESS: CRISP DM

- 3. Data Preparation Phase
- Clean the data i.e. remove any missing values or outliers etc.
- Transform the data
- Select specific data for analysis
- 4. Modeling
- Select appropriate data modelling technique
- 5. Evaluation
- Evaluate the model
- Calculate the accuracy and success rate of the model
- 6. Deployment
- Plan deployment
- Monitor Deployment
- Generate reports to test success of the model



BUSINESS UNDERSTANDING

What is the profound question?

To identify whether the patient is having diabetes or not?

☐ Goal

Goal of this project is to identify the probability of diabetes in patients using data mining techniques.

Advantage of this project

The rules derived will be helpful for doctors to identify patients suffering from diabetes. Further predicting the disease early leads to treating the patient before it becomes critical.



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DATA UNDERSTANDING Iver and insuling i

- ☐ Data Source se metabolic disease
- This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases.
 The objective is to predict based on diagnostic measurements whether a patient has diabetes or not.
- This dataset has 769 samples of diabetic and healthy individuals.
- In particular, all patients here are females of at least 21 years of age.
- The diabetes dataset is credited to UCI machine learning database repository.

- **Data Set Details:**
- The dataset consist of 769 samples, out of which 500 are non diabetic while 269 are diabetic people.
- All patients are females of at least 21 years of age.
- The dataset has total 9 attributes out of which 8 are independent variables and one is the dependent variable i.e. target variable which determines whether patient is having diabetes or not.

Sample Data

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
6	148	72	35	0	33.6	0.627	50	1
1	85	66	29	0	26.6	0.351	31	0
8	183	64	0	0	23.3	0.672	32	1
1	89	66	23	94	28.1	0.167	21	0
0	137	40	35	168	43.1	2.288	33	1
5	116	74	0	0	25.6	0.201	30	0
3	78	50	32	88	31	0.248	26	1
10	115	0	0	0	35.3	0.134	29	0
2	197	70	45	543	30.5	0.158	53	1
8	125	96	0	0	0	0.232	54	1
4	110	92	0	0	37.6	0.191	30	0
10	168	74	0	0	38	0.537	34	1
10	139	80	0	0	27.1	1.441	57	0
1	189	60	23	846	30.1	0.398	59	1
5	166	72	19	175	25.8	0.587	51	1
7	100	0	0	0	30	0.484	32	1
_ n	118	84	47	230	45.8	0.551	21	1

- Attributes Details:
- Pregnancies: No. of times pregnant
- Glucose: Plasma Glucose Concentration a 2 hour in an oral glucose tolerance test (mg/dl)

Normal	Prediabetes	Diabetes	lions store
Below 140 mg/dl	140 to 199 mg/dl	200 mg/dl or more	5

A 2-hour value between 140 and 200 mg/dL is called impaired glucose tolerance. This is called "pre-diabetes." It means you are at increased risk of developing diabetes over time. A glucose level of 200 mg/dL or higher is used to diagnose diabetes.

Blood Pressure: Diastolic Blood Pressure(mmHg)

If Diastolic B.P > 90 means High B.P (High Probability of Diabetes)

Diastolic B.P < 60 means low B.P (Less Probability of Diabetes)

☐ Skin Thickness: Triceps Skin Fold Thickness (mm) —

A value used to estimate body fat. Normal Triceps Skinfold Thickness in women is **23mm**. Higher thickness leads to obesity and chances of diabetes increases.

☐ **Insulin**: 2-Hour Serum Insulin (mu U/ml)

200	Feature	Normal Insulin Level	betes
	2 Hours After Glucose	16-166 mIU/L	

Values above this range can be alarming.

- ☐ **BMI**: Body Mass Index (weight in kg/height in m²)
- Body Mass Index of 18.5 to 25 is within the normal range
- BMI between 25 and 30 then it falls within the overweight range.
- A BMI of 30 or over falls within the obese range.

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□ Diabetes Pedigree Function:

It provides information about diabetes history in relatives and genetic relationship of those relatives with patients. Higher Pedigree Function means patient is more likely to have diabetes.

Age (in years)

Outcome:

Class Variable (0 or 1) where '0' denotes patient is not having diabetes and '1' denotes patient having diabetes.

The dependent variable is whether the patient is having diabetes or not.

- Data preparation stage includes data cleaning and transforming data if needed.
- Various things have to be taken into consideration for data cleaning like:
- Handling Zero/Null Values The zeroes shown in the table are not zeroes but null values. We have deduced this based upon our inference that certain attributes like skin thickness, insulin, BMI etc cannot be zero.

S.No	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	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
5	5	116	74	0	0	25.6	0.201	30	0
6	3	78	50	32	88	31	0.248	26	1
7	10	115	0	0	0	35.3	0.134	29	0
8	2	197	70	45	543	30.5	0.158	53	1
9	8	125	96	0	0	0	0.232	54	1
10	4	110	92	0	0	37.6	0.191	30	0
11	10	168	74	0	0	38	0.537	34	1
12	10	139	80	0	0	27.1	1.441	57	0
13	1	189	60	23	846	30.1	0.398	59	1

The dataset had a lot of zero values.

	Pregnancies	Glucose	BloodPre	ssure	SkinThickness	Insulin	BMI	1
0	6	148.0	72.0	00000	35.00000	95.674746	33.600000	
1	1	85.0	66.0	00000	29.00000	95.674746	26.600000	į.
2	8	183.0	64.0	00000	25.09192	95.674746	23.300000	j
3	1	89.0	66.0	00000	23.00000	94.000000	28.100000	ĺ
4	0	137.0	40.0	00000	35.00000	168.000000	43.100000	j
5	5	116.0	74.0	00000	25.09192	95.674746	25.600000	ĺ
6	3	78.0	50.0	00000	32.00000	88.000000	31.000000	Ė
7	10	115.0	72.5	33517	25.09192	95.674746	35.300000	į.
9	8	125.0	96.0	00000	25.09192	95.674746	32.056663	
10	4	110.0	92.0	00000	25.09192	95.674746	37.600000	j
	DiabetesPedi	greeFuncti	on Age	Outcom	ne			
0		0.6	27 50		1			
1		0.3	31		0			
2		0.6	72 32		1			
3		0.1	67 21		0			
4		2.2	88 33		1			
5		0.2	201 30		0			
6		0.2	248 26		1			
7		0.1	.34 29		0			
9		0.2	232 54		1			
10		0.1	.91 30		0			

The zero values have been replaced by the mean of that column.

Select appropriate attributes for analysis

The dataset consist of 9 attributes i.e. Pregnancies, Glucose, Blood Pressure, Diabetes Pedigree Function, Age, Skin Thickness, Insulin, BMI. These 8 are independent attributes and one i.e. Outcome is the dependent attribute.

As all these attributes affect diabetes so we decided to keep all the independent variables for data mining process.

Data Splitting:

Data was divided into training and testing data into 66.6:33.3 ratio. 2/3rd was training data and
 1/3rd was testing data.

- Different ranges were found out for each continuous variable in the data set. Based upon these ranges categorization was done.
- ☐ The features were categorized as per the below mentioned ranges and were denoted by 0,1, 2 & 3, in order to use them for classification.

Glucose

Plasma Glucose Test	Normal	Prediabetes	Diabetes
2 hour post-prandial	Below 140 mg/dl	140 to 199 mg/dl	200 mg/dl or more
	(0)	(1)	(2)

Blood Pressure(Diastolic)

Ranges	Low	Normal	High
	Below 60	60-90	90 or more
	(0)	(1)	(2)

Skin Thickness

Ranges	Low	Normal	High	tation
	<23	23	>23	
	(0)	(1)	(2)	

Insulin

ĥ	Ranges	Low	Normal	High
jecs:	2 Hours After Glucose	<16 mIU/L	16-166 mIU/L	>166 mIU/L
		(0)	(1)	(2)

BMI(weight in kg/height in m²)

Ranges	Under-weight	Normal	Over-weight	Obese
	<18.5	18.5-25	25-30	>30
	(0)	(1)	(2)	(3)

Diabetes Pedigree Function

Low	Medium	High
0-0.78	0.79-1.561	>1.57
(0)	(1)	(2)

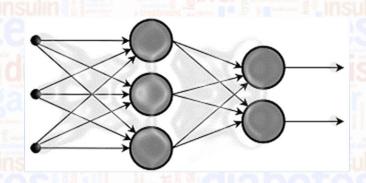
Age

Ы	Ranges	Young	Adult	Old	
		20-44 (0)	44-64 (1)	64-100 (2)	

No. of Pregnancies

Ranges	Normal	Above Normal	Highest	
	<6	6-12	>12	
	(0)	(1)	(2)	

MODELING



☐ This phase includes application of appropriate model to the data.

- Machine Learning Algorithms were used for modeling.
- As we have to classify the data into patients having diabetes or not, I have chosen K-nearest neighbors (KNN), Random decision forests and Artificial neural networks (ANN) to see which one provides us with the best accuracy.

MODELING

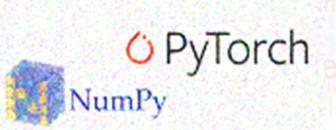
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Software Used:

- Python-Scikit Learn
- Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python.
- ☐ The library is built upon the SciPy (Scientific Python) that must be installed before
 - we can use scikit-learn. This stack includes:
- ☐ **NumPy**: Base n-dimensional array package
- ☐ SciPy: Fundamental library for scientific computing
- ☐ Matplotlib: Comprehensive 2D/3D plotting
- IPython: Enhanced interactive console
- ☐ **Sympy**: Symbolic mathematics
- Pandas: Data structures and analysis













MODELING: USING PYTHON SCIKIT LEARN

The file containing data set is loaded in pandas.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	
0	6	148.0	72.000000	35.000000	79.799479	33.600000	
1	1	85.0	66.000000	29.000000	79.799479	26.600000	
2	8	183.0	64.000000	20.536458	79.799479	23.300000	
3	1	89.0	66.000000	23.000000	94.000000	28.100000	
4	0	137.0	40.000000	35.000000	168.000000	43.100000	
5	5	116.0	74.000000	20.536458	79.799479	25.600000	
6	3	78.0	50.000000	32.000000	88.000000	31.000000	
7	10	115.0	69.105469	20.536458	79.799479	35.300000	
8	2	197.0	70.000000	45.000000	543.000000	30.500000	
9	8	125.0	96.000000	20.536458	79.799479	31.992578	

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	(
2	0.672	32	1
3	0.167	21	(
4	2.288	33	1
5	0.201	30	(
6	0.248	26	1
7	0.134	29	(
8	0.158	53	1
9	0.232	54	1

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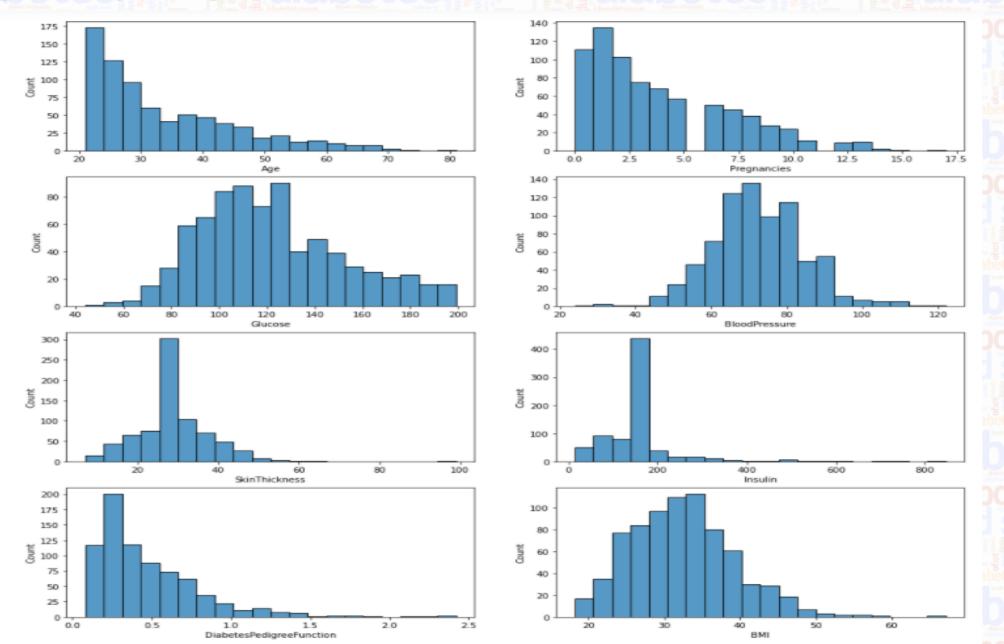
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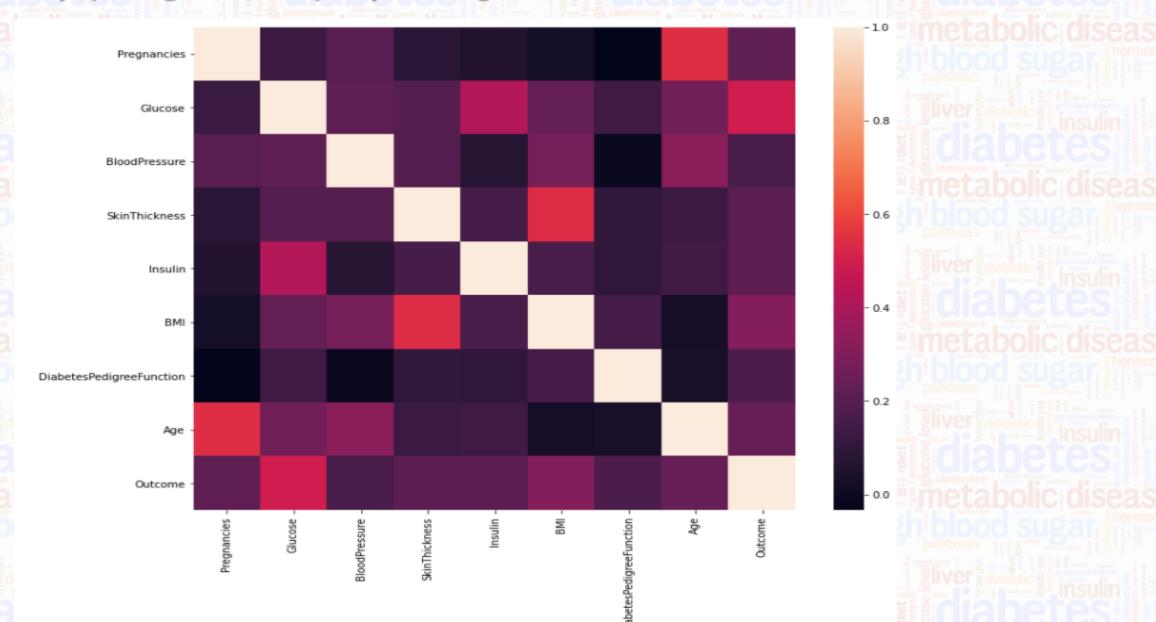
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Histograms explaining the variation of count with different attributes mentioned before



Heatmap (using seaborn) explaining how each attribute is related to the other



Graphs explaining the relationship between each of the parameters metabolic disease metabolic disease metabolic disease



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EVALUATION

CONFUSION MATRIX

		Predicted Yes	Predicted No
Ac	etual	tp (true	fp (false
Ye	es	positive)	positive)
Ac	tual	fn (false	tn (true
No	O	negative)	negative)

Confusion Matrix for KNN

	Predicted Diabetes	Predicted No Diabetes
Actual Diabetes	141	29
Actual No Diabetes	39	47

The Accuracy for KNN is 73%

- •true positives (TP): These are cases in which we correctly predicted diabetes as result.
- •true negatives (TN): We correctly predicted no diabetes and they don't have the disease.
- •false positives (FP): We correctly predicted no diabetes, but they actually had the disease. (Also known as a "Type I error.")
- •false negatives (FN): We correctly predicted diabetes, but they actually had no disease. (Also known as a "Type II error.")

support	f1-score	recall	precision	
170 86	0.81 0.58	0.83 0.55	0.78 0.62	0 1
256 256 256	0.73 0.69 0.73	0.69 0.73	0.70 0.73	accuracy macro avg weighted avg

ALTERNATE MODEL COMPARISON

- ☐ We tried alternate algorithms to compare the accuracy of the model.
- We used Random Forest Classifier and Artificial Neural Network. The results obtained are as under:

Confusion Matrix Random Forest Classifier

	Predicted Diabetes	Predicted No Diabetes	Paperson (
Actual Diabetes	145	25	
Actual No Diabetes	42	44	

	precision	recall	f1-score	support
0	0.77	0.85	0.81	170
1	0.63	0.51	0.56	86
accuracy			0.73	256
macro avg	0.70	0.68	0.69	256
weighted avg	0.73	0.73	0.73	256

Confusion Matrix ANN

	Predicted Diabetes	Predicted No Diabetes
Actual Diabetes	145	25
Actual No Diabetes	34	52

	precision	recall	f1-score	support
0 1	0.86 0.61	0.76 0.76	0.81 0.68	170 86
accuracy macro avg weighted avg	0.74 0.78	0.76 0.76	0.76 0.74 0.76	256 256 256

