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Predict Onset of Diabetes
Big Data System Design - Final Report

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Outline

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Introduction

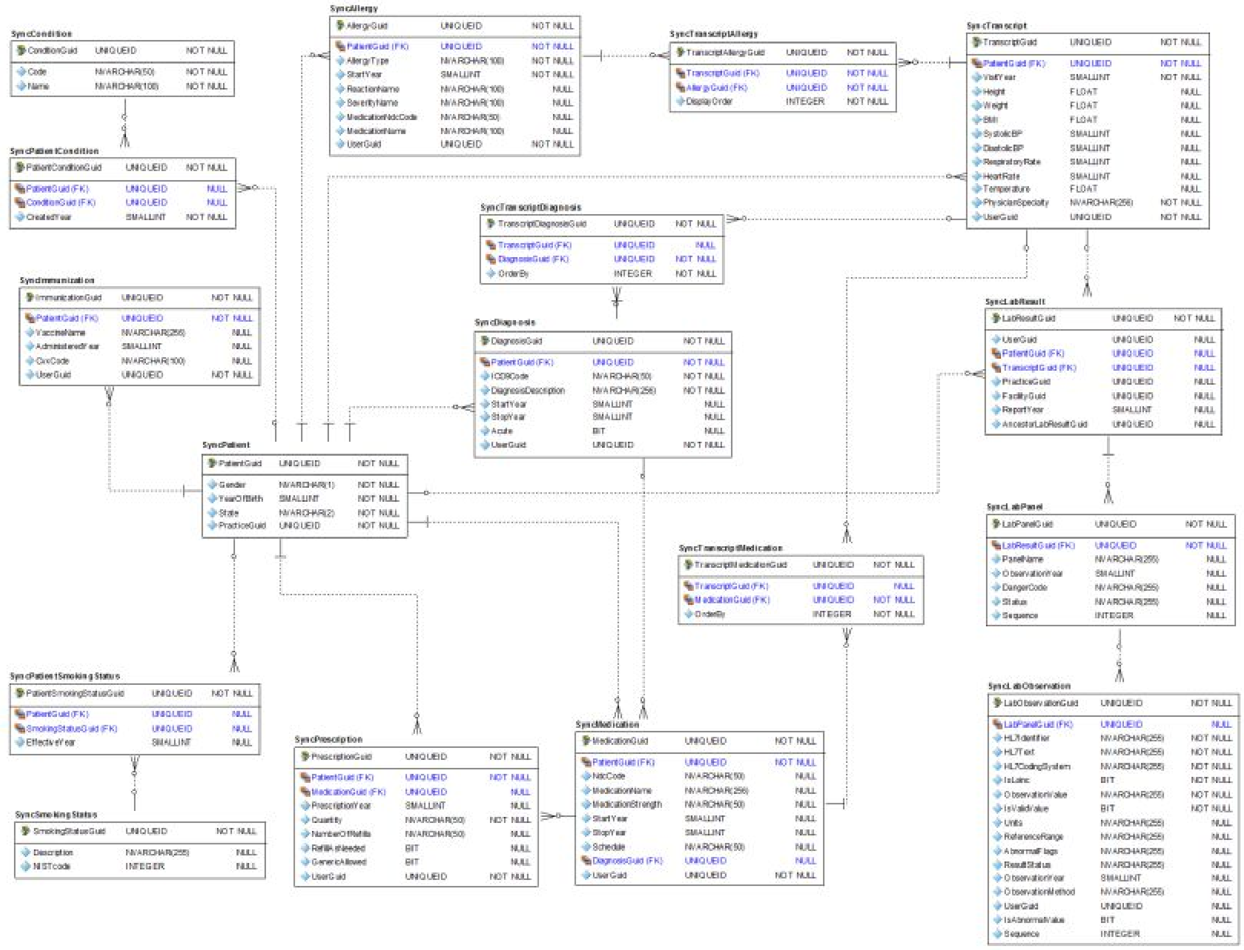
The research/development question is to predict based on diagnostic measurements whether a patient has type 2 diabetes using the Kaggle based Practice Fusion Diabetes Classification dataset.

The CSV text dataset contains records of 10,000 de-identified medical records. Data includes pregnancy count, glucose concentration, blood pressure, tricep skinfold thickness, insulin resistance, body mass index, diabetes family history factor, age, and diabetes positive.

The ultimate goal of your proposed system is to perform this prediction in an automated way using big data system design.

Hadoop big data ecosystem was used (MongoDB, Machine Learning, Processing techniques such as MapReduce, Keras, TensorFlow).

Practice Fusion De-Identified Data Set



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ConditionGuid (FK)	UNIQUEID	NULL
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SyncImmunization

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PatientGuid (FK)	UNIQUEID	NOT NULL
VaccineName	NVARCHAR(255)	NULL
AdministeredYear	SMALLINT	NULL
CvxCode	NVARCHAR(100)	NULL
UserGuid	UNIQUEID	NOT NULL

SyncAllergy

AllergyGuid	UNIQUEID	NOT NULL
PatientGuid (FK)	UNIQUEID	NOT NULL
AllergyType	NVARCHAR(100)	NOT NULL
StartYear	SMALLINT	NOT NULL
ReactionName	NVARCHAR(100)	NULL
SeverityName	NVARCHAR(100)	NULL
MedicationNdcCode	NVARCHAR(50)	NULL
MedicationName	NVARCHAR(100)	NULL
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SyncTranscriptAllergy

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DisplayOrder	INTEGER	NOT NULL

SyncTranscript

TranscriptGuid	UNIQUEID	NOT NULL
PatientGuid (FK)	UNIQUEID	NOT NULL
VisitYear	SMALLINT	NOT NULL
Height	FLOAT	NULL
Weight	FLOAT	NULL
BMI	FLOAT	NULL
SystolicBP	SMALLINT	NULL
DiastolicBP	SMALLINT	NULL
RespiratoryRate	SMALLINT	NULL
HeartRate	SMALLINT	NULL
Temperature	FLOAT	NULL
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SyncTranscriptDiagnosis

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DiagnosisGuid (FK)	UNIQUEID	NOT NULL
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SyncDiagnosis

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PatientGuid (FK)	UNIQUEID	NOT NULL
ICD9Code	NVARCHAR(50)	NOT NULL
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UserGuid	UNIQUEID	NOT NULL

SyncLabResult

LabResultGuid	UNIQUEID	NOT NULL
UserGuid	UNIQUEID	NULL
PatientGuid (FK)	UNIQUEID	NULL
TranscriptGuid (FK)	UNIQUEID	NULL
PracticeGuid	UNIQUEID	NULL
FacilityGuid	UNIQUEID	NULL
ReportYear	SMALLINT	NULL
AncestorLabResultGuid	UNIQUEID	NULL

SyncPatient

PatientGuid	UNIQUEID	NOT NULL
Gender	NVARCHAR(1)	NOT NULL
YearOfBirth	SMALLINT	NOT NULL
State	NVARCHAR(2)	NOT NULL
PracticeGuid	UNIQUEID	NOT NULL

SyncLabPanel

LabPanelGuid	UNIQUEID	NOT NULL
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PanelName	NVARCHAR(255)	NULL
ObservationYear	SMALLINT	NULL
DangerCode	NVARCHAR(255)	NULL
Status	NVARCHAR(255)	NULL
Sequence	INTEGER	NULL

SyncTranscriptMedication

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MedicationGuid (FK)	UNIQUEID	NOT NULL
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SyncPatientSmokingStatus

PatientSmokingStatusGuid	UNIQUEID	NOT NULL
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SmokingStatusGuid (FK)	UNIQUEID	NULL
EffectiveYear	SMALLINT	NULL

SyncSmokingStatus

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NISTcode	INTEGER	NULL

SyncPrescription

PrescriptionGuid	UNIQUEID	NOT NULL
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MedicationGuid (FK)	UNIQUEID	NULL
PrescriptionYear	SMALLINT	NULL
Quantity	NVARCHAR(50)	NOT NULL
NumberOfRefills	NVARCHAR(50)	NULL
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GenericAllowed	BIT	NULL
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SyncMedication

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MedicationName	NVARCHAR(255)	NULL
MedicationStrength	NVARCHAR(50)	NULL
StartYear	SMALLINT	NULL
StopYear	SMALLINT	NULL
Schedule	NVARCHAR(50)	NULL
DiagnosisGuid (FK)	UNIQUEID	NULL
UserGuid	UNIQUEID	NOT NULL

SyncLabObservation

LabObservationGuid	UNIQUEID	NOT NULL
LabPanelGuid (FK)	UNIQUEID	NULL
HL7Identifier	NVARCHAR(255)	NOT NULL
HL7Text	NVARCHAR(255)	NOT NULL
HL7CodingSystem	NVARCHAR(255)	NOT NULL
IsLoinc	BIT	NOT NULL
ObservationValue	NVARCHAR(255)	NOT NULL
IsValidValue	BIT	NOT NULL
Units	NVARCHAR(255)	NULL
ReferenceRange	NVARCHAR(255)	NULL
AbnormalFlags	NVARCHAR(255)	NULL
ResultStatus	NVARCHAR(255)	NULL
ObservationYear	SMALLINT	NULL
ObservationMethod	NVARCHAR(255)	NULL
UserGuid	UNIQUEID	NULL
IsAbnormalValue	BIT	NULL
Sequence	INTEGER	NULL

Motivations

- This is interesting question for us due to a lot of our family members have diabetes
- It is important to develop a system to be able to predict the occurrence of diabetes if the patient’s lifestyle and eating habits are kept the same and possibly prevent the occurrence of diabetes if preventative steps are taken by patient
- 415 million people have diabetes worldwide
- 8.3% of the world adult population (equal parts men/women) have diabetes and is rising
- Diabetes doubles a person's risk of early death.
- 5 million deaths occur worldwide each year because of diabetes.
- The global economic cost of diabetes is estimated to be US $612 billion.

Related Work

The following are sources of existing research/development work has tried to answer the same or a similar question:

- https://www.kaggle.com/c/pf2012-diabetes (data set)
- Using the ADAP learning algorithm to forecast the onset of diabetes mellitus
- Developing risk prediction models for type 2 diabetes: a systematic review of methodology and reporting

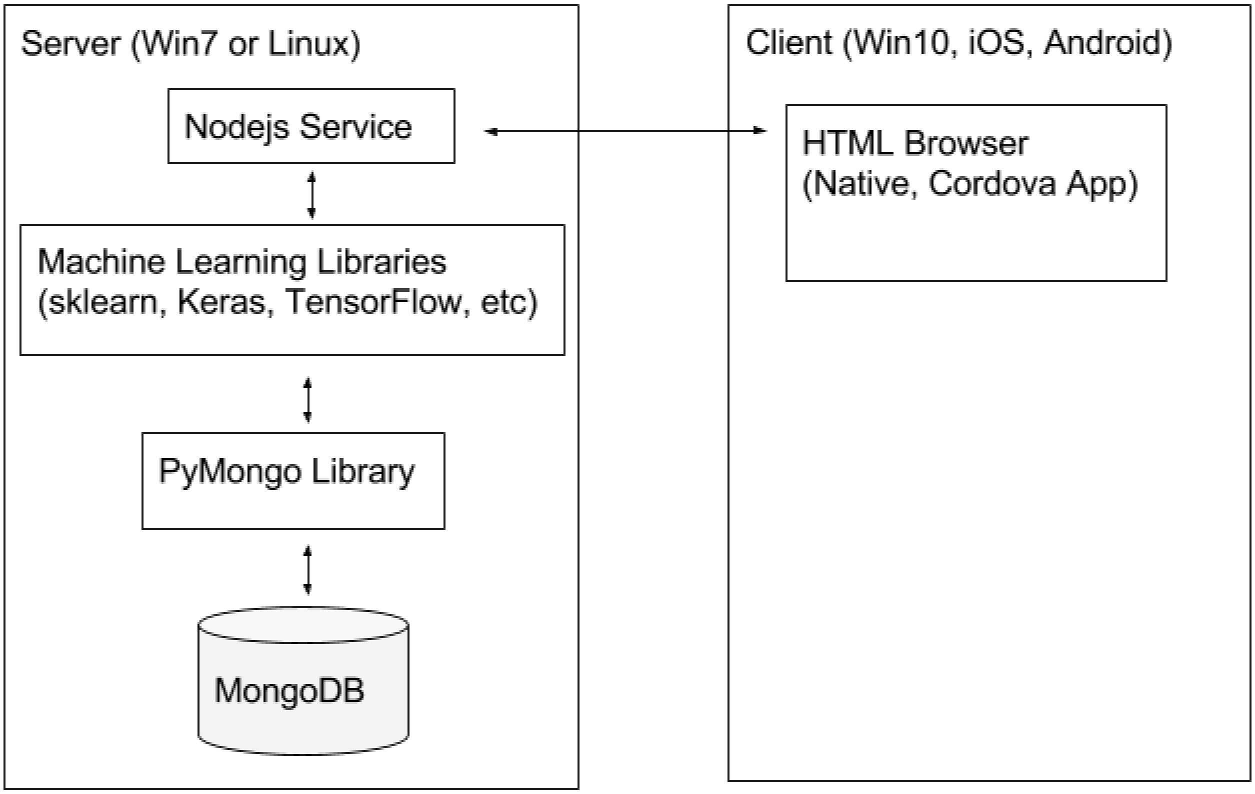
A highly reliable and accurate automated prediction algorithm is still not available.
Also, it would be self-evident that an accurate automated prediction algorithm should work regardless of gender and ethnic background.

Proposed Approach

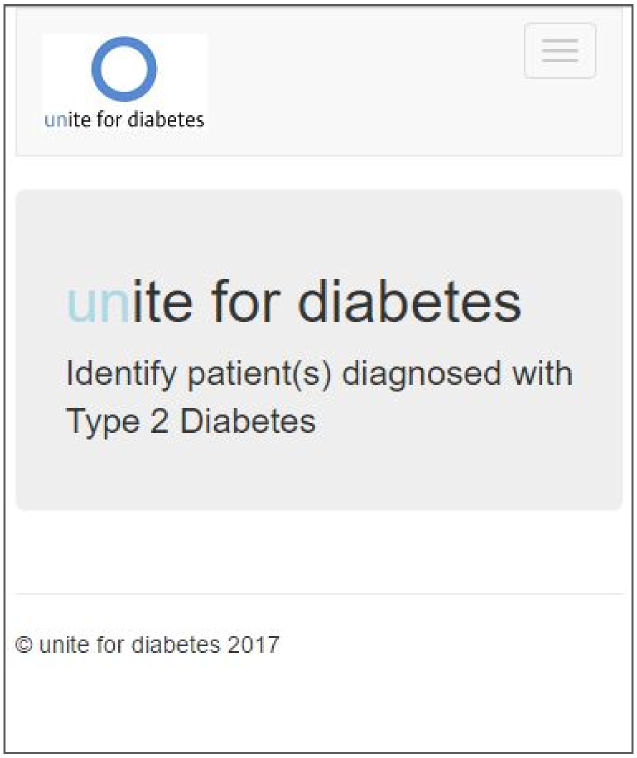
- Plan for working out the solutions to the question:
- Research dataset
  - Survey knowledge experts (UML doctor, nursing staff, and people with the diabetes)
  - Improve via algorithms accuracy and precision level on missing values
  - Research ML algorithms, current solutions on kaggle.com
  - Use rapidminer.com, and Python ML libraries
  - Performance test ML algorithms
- Main features in your proposed system:
  - Hadoop based backend (HDFS, MongoDB (i.e. NoSQL DB), Python, Apache Web Server)
  - HTML5, JS, Cordova mobile development front end (desktop, iOS, Android)
  - Data entry and/or upload data set
  - Matplotlib, plotly, Google Chart, D3, etc.
  - Based on input data, one or more users can be told whether or not he/she has or is susceptible to get type 2 diabetes (data can be optionally added to learning dataset to improve algorithm accuracy)
- Implementation approach:
  - MongoDB
  - Python, RapidMiner
  - HTML5 - JS
  - NN (Spark, Keras, TensorFlow), Scikit Learn, MapReduce
  - Machine Learning Algorithm(s) (Classification, Regression, Clustering, Dimensionality reduction, Model selection, Preprocessing) - those found exhibiting best performance
    - Keras based neural network
    - Gaussian Naive Bayes
    - K-Nearest Neighbor Classifier
    - Decision Tree Classifier

- Random Forest Classifier
- Ada Boost Classifier
- Gradient Boosting Classifier

Block Diagram



Mobile Application



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Identify patient(s) diagnosed with Type 2 Diabetes

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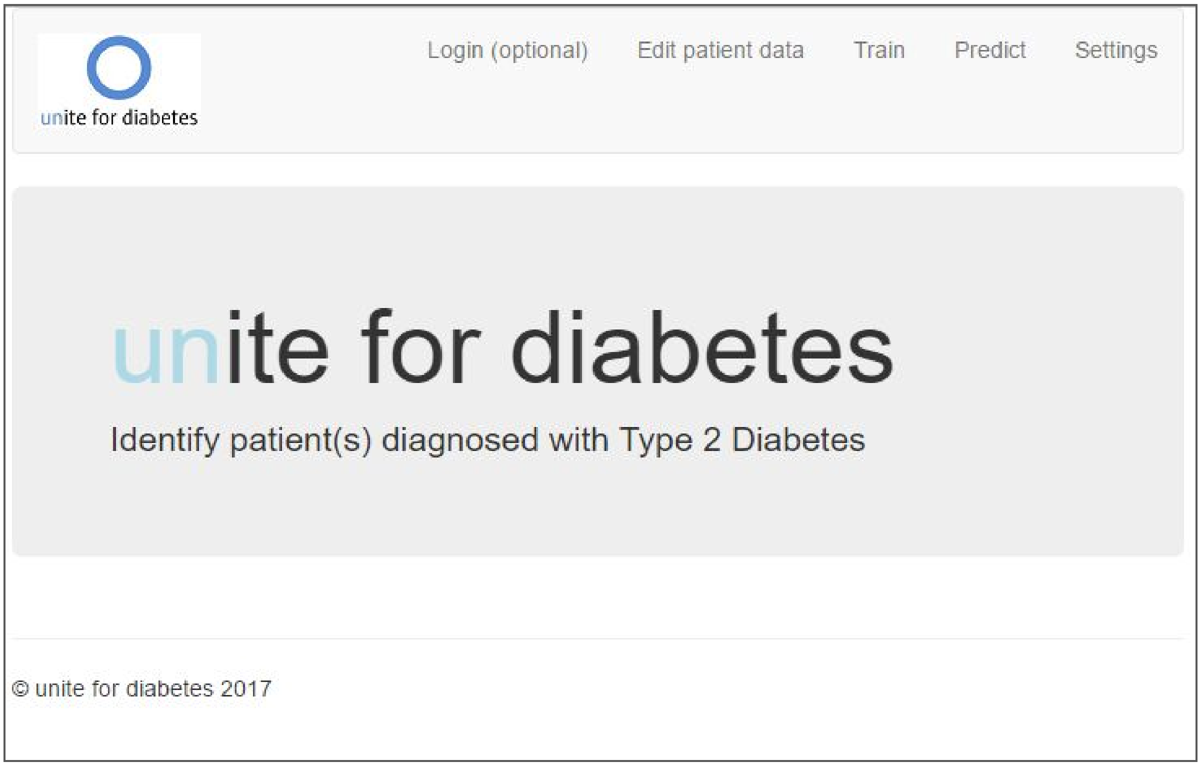
Tablet/Desktop Application



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Identify patient(s) diagnosed with Type 2 Diabetes

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Evaluation

We evaluated our solution as follows (to demonstrate that our solution/answer is good/reasonable):

- Test ML algorithms locally with the stock dataset
- Preprocess dataset
- Find the algorithm that performs the best in a reasonable amount of processing time at a small scale first
- Setup a MongoDB environment to handle the increase in size
- Integrate MongoDB component
- Test the scaled up components at the backend server side
- Test the scaled up components at the client side
- Compare all results with those available online in previous studies
- Publish results on sites like github and kaggle.com to verify and respond to feedback

Timeline

- Week 1 (ending 2017-02-02) - Proposal presentation
- Week 2 (ending 2017-02-09) - Pre data set analysis and Github setup
- Week 3 (ending 2017-02-16) - Subject matter expert surveys
- Week 4 (ending 2017-02-23) - ML algorithm analysis
- Week 5 (ending 2017-03-02) - ML algorithm testing
- Week 6 (ending 2017-03-09) - ML algorithm testing
- Week 7 (ending 2017-03-16) - Scale up dataset
- Week 8 (ending 2017-03-23) - Hadoop ecosystem integration
- Week 9 (ending 2017-03-30) - Data plot development
- Week 10 (ending 2017-04-06) - Front end development
- Week 11 (ending 2017-04-13) - System performance testing
- Week 12 (ending 2017-04-20) - System performance testing
- Week 13 (ending 2017-04-27) - Final presentation

Experimental Results and Discussions

Discuss the research/development results and quantify the performance study

Conclusions and Future Work

Summarize your work, give your conclusions if possible, and point out the possible future work (how the work can be further improved/extended)

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