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Using supervised learning for the binary classification of Type 2 Diabetes

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CMP6202 - Artificial Intelligence & Machine Learning

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Contents

Abstract

Probably would benefit from an abstract. You can't really write this until the very end though, so return to it then. **The example work is from a previous year wherein this assessment was a group task. You can see that each group member developed one ML model, but you seem to be developing all of them yourself, so don't be mislead by the report titles only mentioning one model.**

Your EDA can be very extensive, and you could potentially have pages and pages and pages of it; this isn't a bad thing. The vast majority of any ML-related work is EDA because it gives you the background information on the dataset to then apply when training the model, such as the identification of non-numerical columns and encoding them into numerical equivalents where possible so that they become useful training data for the model, as ML models cannot interpret strings.

Notes, remove before final

0.1 Mihai W7

0.1.1 Overall notes - Beginning of talk

- Find a problem before a dataset (No)
- Identify if said problem is regression or classification
- It's hard to use a classification dataset where the target column is just a bunch of labels (???)
  - This may be in reference to Week 7's wine set where you had 7 different levels of quality but converted them to 2 for binary classification.
- Examples on Moodle
- Datasets on Moodle but it's almost 100% that someone else will have used them.
- I also don't know if you're even allowed to use them.
- A dataset can have more than one target column (though the ones you use likely won't).
- Mihai strongly warns that ML is a very iterative process, and your first attempt will probably be poor.
  - This is why you use **pipelines** as in CMP6230 but that's not this module.
- You will be asked questions on it in the presentation **RELATED TO WHAT YOU'VE DONE IN CLASS**, likely by Mihai himself, and he is trying to catch you out.

0.1.2 Section 2

- After you have an identified dataset, begin EDA.
- Describe how you split the dataset into training and testing dataset.
- If the machine sees the test data, it may "overfit".
  - You've seen this before where the line of best fit isn't really a line and just connects every single point, meaning it's really good at guessing the data it already knows but not new data.
- You split your data *BEFORE* EDA to avoid "conceptual overfitting".
- When splitting data, you need to think about data imbalance i.e. training set having too much of the one option and few of the other (too many True, not enough False).
- SKLearn may try to fix that for you.
- Identify outliers, missing data.

- "Missing information can be information in itself". Consider the source of the data (not Kaggle but rather where the Kaggle author got it from)
  - You might be able to impute data rather than deleting it.
  - Conserve as much data as you can, deleting data should be a last option.
- Erroneous data
  - Another reason why your data source is important.
  - Could just be mistyped, see what the erroneous data actually is to see if you can correct it.
- Outliers
  - Is it significant enough to remove it? Is it definitely an outlier; could it feasibly be true? (speed camera example where one guy went 30 but another went 100, but that's still plausible.)
  - Boxplots can identify outliers.
- If your dataset is bad, your model will be, too.

0.1.3 Section 3

- Identify the right algorithm.
  - Decision trees are good at classification.
  - Random forest is also used for it.
  - Naive Bayes and KNN work for prediction and classification.
  - Some of these may perform worse with higher amounts of data, look into them.
- Performance won't matter a massive amount but you still need to be able to justify why it was good.
  - Also justify its downsides and limitations.
  - And the limtiations of the dataset itself.

0.1.4 Section 4

- Encoding is important here because ML doesn't use text.
  - Side-note: Even if it does that's actually just an abstraction and it's just encoding it under the hood.
- Fine-tuning
  - Playing around with parameters of the functions.
  - KNN Neighbours and such

  - Often comes after an initial test run
  - If your accuracy is really low (20% was the example), fine-tuning won't help and you just need to redo the entire work.
  - Could maybe give you an extra 5% accuracy.
  - Decision trees may have multiple versions. SKLearn's decision tree may be different from a CUDA one.

- Evaluation metrics
  - Accuracy is not Precision. Which do you need?
  - You want both to be high, if one lags massively behind the other then that's bad.
  - ML is an iterative process until you can get the best performing model.

0.1.5 Section 5

- Visualisation of evaluation results
  - For a correlation matrix, a heatmap is better than a bar plot for example.

Introduction

Diabetes mellitus, or type 2 diabetes, accounts for 90% of the 4.4 million cases of diabetes in the UK, and it is estimated that there are 1.2 million undiagnosed cases of type 2 diabetes across the country (Diabetes UK, 2024). The rate of type 2 diabetes per 100,000 individuals is rapidly increasing, with Khan et al. (2020)'s analysis projecting that by 2030, the rate will reach 7,079 per 100,000. Many people with diabetes suffer immensely reduced quality of life, with approximately 50% of patients suffering from peripheral neuropathy (Dhanapalaratnam et al., 2024), an irreversible disability which causes immense pain due to nerve damage from high blood sugar (NHS, 2022), which can occur when the patient was unaware they even had diabetes.

Therefore, it is imperative that systems are put in place to enable the swift diagnosis of diabetes, especially type 2 diabetes given its major prevalence. This can be accomplished by training machine learning models on existing clinical datasets to identify common trends in those with and without type 2 diabetes. This report will document the planning, development and evaluation of multiple machine learning models in their classification of whether individuals have type 2 diabetes based on multiple clinical factors, specifically through the stages of:

- Dataset Identification
- Data Preprocessing
- Data Wrangling
- Exploratory Data Analysis (EDA)
- Model Development
- Model Evaluation
- Research Conclusions

1.1 Dataset Identification

Machine learning models require large amounts of data to train upon, meaning a dataset must be identified consisting of many rows and features. This project identified two datasets which could be wrangled into one larger dataset, the first of which being the well-reputed Pima Indian[1] Diabetes Database (UCI Machine Learning, 2024), sourced from Kaggle, a platform for students and researchers alike to download and upload datasets and code for research purposes. The dataset contains data on Pima Indian women in Phoenix, Arizona, USA, and has previously seen wide use across academic literature relating to machine learning (AlZu'bi et al. (2023), Zou, Zhang, and Chen (2024), Joshi and Dhakal (2021), Hayashi and Yukita (2016)), where other researchers have also aimed to solve the problem of diabetes classification via supervised learning. This dataset contains 768 rows with 9 features.

This project also includes a second dataset, also from Kaggle, that has been previously used in literature by Zou, Zhang, and Chen (2024). This dataset (John DaSilva, 2024) is based on data from female patients in Frankfurt, Germany, and includes the same 9 features as the Pima Indian dataset, but includes 2000 rows. By wrangling these two datasets into one larger dataset of 2768 rows, it will be possible to give the machine learning models more data to train upon.

Table 1.1 details the 9 features seen in both datasets and their descriptions.

Feature	Description
Pregnancies	The number of pregnancies the patient has had.
Glucose	Plasma glucose concentration over 2 hours in an oral glucose tolerance test.
BloodPressure	Diastolic blood pressure in mm/Hg.
SkinThickness	Triceps skin fold thickness (mm)
Insulin	2-hour serum insulin.
BMI	Body Mass Index, calculated from the patient's weight and height.
DiabetesPedigreeFunction	The product of a function to ascertain the probability of diabetes based on family genetics. (Akmeşe, 2022)
Age	The patient's age.
Outcome	Whether the patient is likely to develop diabetes.

Table 1.1: The features seen in both datasets.

[1] "Pima Indian" refers to a specific Native American ethnic group rather than people from India.

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