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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.

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, 2024a). 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 Integration
- Data Preprocessing
- 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 integrated into one larger dataset, the first of which being the well-reputed Pima Indian Diabetes Database (UCI Machine Learning, 2024), downloaded from Kaggle, a platform for students and researchers alike to download and upload datasets and code for research purposes. The data originates from the National Institute of Diabetes and Digestive and Kidney Diseases, who collected this data from Pima Indian[1] women aged 21 and over in hospitals in Phoenix, Arizona, USA, and it 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 integrating 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.

1.2 Supervised learning task identification

As previously mentioned, it is possible for patients to have diabetes without knowing. Therefore, it is paramount that swift and simple diagnosis methods are put in place, which can be achieved through the use of supervised learning classification models. This requires the existence of the "ground truth", which refers to the label given to data that indicates its class (c3.ai, 2024). Within these datasets, the ground truth is present as the 'Outcome' feature, which will be used as the target variable for the produced classification models.

Exploratory Data Analysis

This chapter details the EDA processes undertaken with the datasets, including key questions that will be answered by the process, as well as the splitting of the data into training and testing sets.

2.1 Data Integration

The two datasets must first be merged into one to allow for an overall analysis to be performed. This is a simple process because they both contain the same 9 features, and is detailed in Figure 2.1.

```
pima_df = pd.read_csv("Data/pima.csv")
pima_df.shape
```
✓ 0.0s
```
(768, 9)
```

```
frankfurt_df = pd.read_csv("Data/frankfurt.csv")
frankfurt_df.shape
```
✓ 0.0s
```
(2000, 9)
```

```
df = pd.concat([pima_df, frankfurt_df], axis = 0, ignore_index = True)
df.shape
```
✓ 0.0s
```
(2768, 9)
```

Figure 2.1: Integrating the two separate datasets into one larger dataset.

2.2 Question identification and assumptions

The key factors involved in the diagnosis of diabetes are critical to understand, which can be solved through EDA on these datasets. It is possible to make various assumptions based on topical background research of each of the features in the dataset, detailed in Table 2.1

Feature	Research-based assumptions
Pregnancies	Approximately 13.4% of pregnant women develop a temporary condition known as Gestational Diabetes Mellitus (GDM), which typically subsides after birth (Adam et al., 2023). However, research by (Dennison et al., 2021) indicates that 33% of women who develop GDM will go on to develop permanent diabetes mellitus within 15 years. Therefore, it is assumed that pregnancies will positively correlate with the diabetes outcome. It is also expected that pregnancies should naturally positively correlate with age.
Glucose	Glucose concentrations are an enormous factor in the diagnosis of diabetes mellitus, being one of the main metrics used to certify the condition, where results over 200mg/dL mean an absolute diagnosis[1] (Aftab et al., 2021). It is therefore assumed that the glucose concentrations will be one of the strongest influences of the outcome, and that it will also correlate heavily with insulin levels.
BloodPressure	Diastolic blood pressure (DBP) does influence the diagnosis of diabetes mellitus, as 56.2% of recently diagnosed patients presented with elevated DBP in Nelaj et al. (2023)'s limited study of 126 patients, but it is not a decisive factor by itself. Therefore, it is assumed that there will be some correlation between DBP and the outcome, but not as major as other factors like plasma glucose levels.
SkinThickness	It is a frequent assumption even non-academically that people who weigh more, and by consequence have higher skin thickness in certain areas such as the triceps, have a higher risk of developing conditions like type 2 diabetes. This is backed by a study by Ruiz-Alejos et al. (2020), which found strong associations between skin thickness and diabetes mellitus, as well as high blood pressure. Therefore, it is assumed that there will be a strong correlation between tricep skin thickness and the outcome, as well as an expectation of strong correlations between thickness, BMI and blood pressure.
Insulin	Diabetes mellitus is directly associated with insulin deficiency, and as such, it is assumed that this factor will be the strongest influence in the outcome. This is because 2-hour serum insulin tests, as used in this dataset, are frequently part of HOMA-IR[2] assessments.

[1]The other main metric is insulin deficiency, meaning that the patient could have glucose levels lower than 200mg/dL and still be diagnosed if they are instead insulin deficient. (Aftab et al., 2021).

[2]Homeostasis Model Assessment of Insulin Resistance, used to measure insulin resistance (Tahapary et al., 2022), which can be used in both type 1 and type 2 diabetes diagnosis (Khalili et al., 2023).

BMI	BMI is likely to be a significant factor in the outcome, which is backed by previous academic studies indicating that 71% of studied individuals showed increases in BMI prior to diagnosis (Donnelly, McCrimmon, and Pearson, 2024). Additionally, BMI is used in insulin resistance measurement assessments, which are key assessments in diabetes diagnosis, meaning that it is a safe assumption that BMI will be a large factor in the outcome.
DiabetesPedigree-Function	People are more likely to develop diabetes mellitus if there is a family genetic history of the condition, though it is not directly caused by any one particular gene (Diabetes UK, 2024b). With the pedigree function aiming to quantify the inheritance probability, it can be assumed that it will likely correlate heavily with the outcome.
Age	Suastika et al. (2012) studied the effects of age as a risk factor for diabetes mellitus, finding that many natural associated factors of ageing including increases in body fat and decreases in lipid metabolism had considerable influence on the development of insulin resistance and diabetes mellitus by consequence. Therefore, it is likely that there will be a noticeable correlation between a patient's age and the outcome.

Table 2.1: Research-based assumptions prior to any EDA.

Based on these assumptions, the questions that this EDA process aims to answer are:

ID	Research-based assumptions
1	Are there any missing values or values that are not physically possible?
2	Are there any significant outliers?
3	Is the dataset evenly balanced in terms of the outcome? If not, what should be done?
4	Does the rate of diabetes positively correlate with the amount of pregnancies a woman has had?
5	Do the amount of pregnancies influence any of the other features?
6	What is the distribution of blood glucose levels in patients with and without diabetes?
7	Does BMI influence glucose levels?
8	Is diastolic blood pressure a worthwhile diagnosis method in this dataset?
9	Is the average skin thickness of those with diabetes actually higher than those without?
10	How does the relationship between insulin and glucose change between those with and without diabetes?

Table 2.2: The questions that this EDA process aims to answer.

2.3 Splitting the dataset

2.4 EDA process and results

2.5 EDA conclusions

Experimental Design

This chapter details the planned algorithms to be leveraged against this dataset, as well as the metrics to evaluate them. Furthermore, the data cleaning and preprocessing stages will be deeply explored, as well as some potential limitations relating to their use.

3.1 Identification of chosen algorithms

3.2 Identification of appropriate evaluation techniques

3.3 Data Cleaning and Pre-processing Transformations

3.4 Limitations and Options

Model Development

This chapter details the training and evaluation processes of the original produced models before any iterative improvements such as hyperparameter tuning.

4.1 Predictive modelling process

4.2 Results on seen data

Evaluation and further improvements

This chapter details the extensive evaluation of each model, as well as iterative improvements that were made to enhance their performance.

Conclusion

6.1 Summary of results

6.2 Reflection on Individual Learning

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