

Predicting the Presence of Diabetes with Binary Classification

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Introduction to Artificial Intelligence

November 20, 2024

Preface

My Google Colab notebook for this report can be located at this link:

<https://colab.research.google.com/drive/1D6BkQLUZJLphRX6dAUOU1cKbllYoRMyQ?usp=sharing>.

1 Abstract

Diabetes is a common disease that affects roughly 12 percent of the American population^[1]. It occurs in two different ways: Type I diabetes attacks the immune system, preventing the body from producing insulin; type II diabetes causes the body to intercept any amount of insulin, each though it may produce enough of it^[2]. In either case, the human body's inability to utilize insulin is caused by one's excessive consumption of glucose. It can be easy for an individual to consume too many sugary foods and beverages. This issue is particularly noteworthy for Americans because a concerning amount of food relies on high fructose corn syrup and excess sugar. A simple task that we do everyday can cause a person to end up like the 1.6 million people who passed away from diabetes in 2021^[3]. Many factors, such as exercise, drug use, and cholesterol can help infer the presence of diabetes. For this reason, an artificial intelligence project based on predictive neural networks can help one survey the correlation and importance of these factors.

The intent of this project is to predict the presence of diabetes among hospital patients. The process of making these predictions can be defined as a binary classification problem, with a **0** for *non-diabetic* or a **1** for *diabetic/pre-diabetic*. Real-life patient data will be analyzed with logistic regression-based neural networks to make such predictions. An overfitting model will be created first to memorize the patient data, which consists of 21 questionnaire-based features. Several other models will be created to determine the optimal configuration for predicting the presence of diabetes. Once the ideal model is determined, each individual feature will be trained on the model, and features that appear unimportant will be incrementally removed from the prediction process.

2 Data Exploration

The "Diabetes Health Indicators Dataset" was gathered from a data collection website called Kaggle^[4]. It was also archived from the UC Irvine Machine Learning Repository^[5]. The dataset contains 70,692 samples: exactly 50.0% of the dataset's samples are classified as *non-diabetic*, while the remaining 50.0% are labelled as *diabetic/pre-diabetic*.

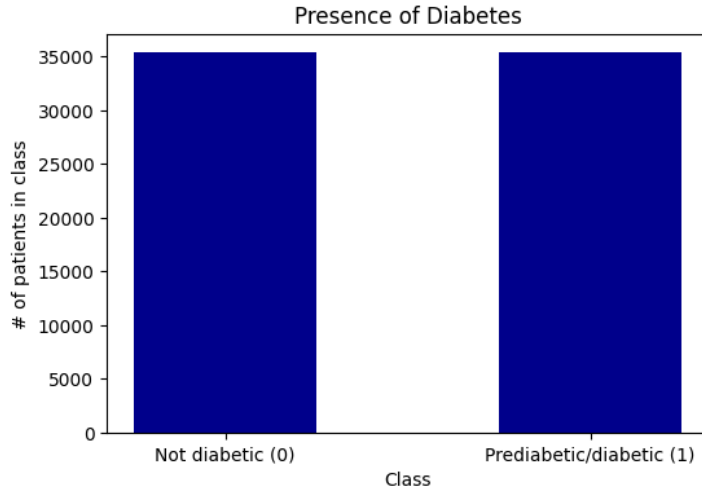


Figure 1: A breakdown of the quantity of features in each class. The **Not diabetic (0)** class contains 35,346 samples, while the **Prediabetic/diabetic (1)** class contains 35,346 samples as well.

Within each sample is a series of 21 features and 1 target variable. Each feature represents a piece of information gathered from a patient by a medical professional at a hospital. The target variable represents the presence of diabetes; it is the job of neural network models to correctly predict whether a patient has diabetes based on the information given from the 21 features.

Attribute	Description
1 Diabetes_binary	Does patient have diabetes? (TARGET VARIABLE)
2 HighBP	Is patient's blood pressure high?
3 HighChol	Is patient's cholesterol high?
4 CholCheck	Did patient get a cholesterol check in the past 5 years?
5 BMI	What is the patient's body mass index ?
6 Smoker	Does patient smoke ?
7 Stroke	Did patient have a stroke ?
8 HeartDiseaseorAttack	Did patient ever have a heart attack ?
9 PhysActivity	Did patient exercise in the last 30 days?
10 Fruits	Does patient regularly eat fruit ?
11 Veggies	Does patient regularly eat vegetables ?
12 HvyAlcoholConsump	Does patient drink a lot of alcohol ?
13 AnyHealthcare	Does patient have health coverage ?
14 NoDocbcCost	Did patient need to see a doctor but couldn't?
15 GenHlth	How is patient's overall health ? (1 to 5)
16 MentHlth	How many days (0-30) did patient have poor mental health ?
17 PhysHlth	How many days (0-30) did patient have poor physical health ?
18 DiffWalk	Does patient struggle with climbing up stairs ?
19 Sex	What is patient's sex ?
20 Age	What is patient's age ?
21 Education	What is patient's education ?
22 Income	What is patient's income ?

Figure 2: A complete list of features from the "Diabetes Health Indicators Dataset," each with descriptions^[6]. **Diabetes_binary** serves as the target variable that a model needs to predict.

Out of the 21 features, 14 of them contain binary data, while 7 of them contain continuous data. The features' distributions are visualized in Figure 3 and Figure 4 below:

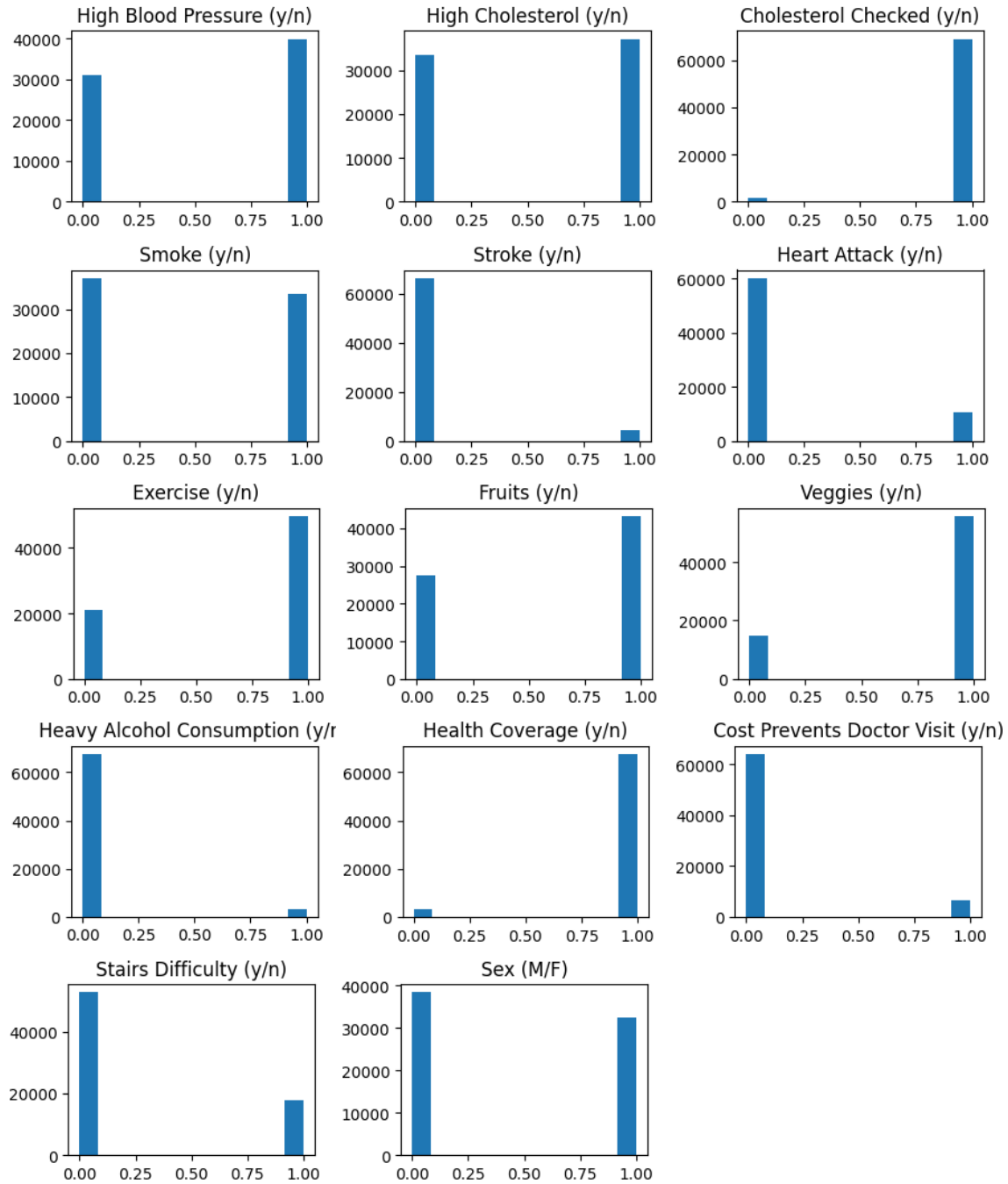


Figure 3: Histograms visualizing the distribution of the 14 features from the "Diabetes Health Indicators Dataset." These particular features are *binary*, meaning that **0** resembles *no* and **1** resembles *yes*. For the **Sex (M/F)** feature, 0 represents "female" while 1 represents "male." The features' names were changed slightly from Figure 2's names to provide a cleaner data visualization.

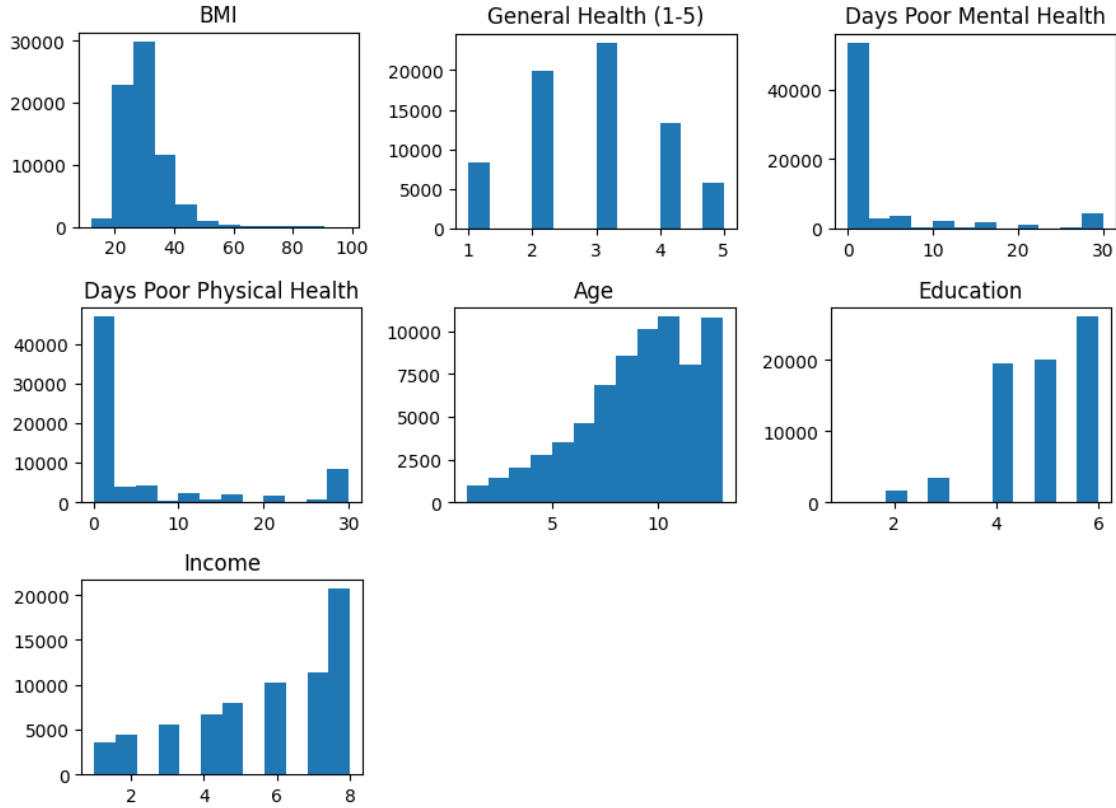


Figure 4: Histograms visualizing the distribution of 7 more features from the "Diabetes Health Indicators Dataset." Unlike the 14 features in Figure 3, these histograms consist of more than two values.

The last three features from Figure 4—Age, Education, and Income—contain some seemingly nonsensical values. However, the values of Age (1 through 13), Education (1 through 6), and Income (1 through 8) are categorical. The specific categorizations of these feature quantities can be observed by navigating to these websites: *ResearchGate*^[7] for the **Age** categorization, the *National Addiction & HIV Archive Program*^[8] website for the **Education** classification, and the *Resource Center for Minority Data*^[9] website for the **Income** categorization. These websites are located in the References section under Numbers 7, 8, and 9.

Data Normalization

The 21 features underwent a normalization calculation to facilitate the performance for all potential models. The target variable **Diabetes_binary** was not included in the calculation due to its variables already containing binary values. The calculation for each feature's value was conducted by using a *z-score* calculation, which is represented like this:

$$z - score = \frac{x - \mu}{\sigma}$$

where x is a feature's current value inside a row, μ is the standard mean of the feature, and σ is the feature's standard deviation. The *z-score* serves as the result that replaces the raw value inside the feature's instance. This calculation is performed iteratively for every value inside of each feature. This process reduces the minimum-maximum range for each of the 21 features, which will tentatively allow each model to perform more quickly with more robust metrics.

3 Overfitting the Data

The data overfitting process is crucial for ensuring a neural network model can effectively memorize the data. If a model can accomplish this task, then it should eventually perform reasonably well with a training/validation split of the data. A large neural network with a **512-256-64-32-16-1 architecture** served as the ideal model for overfitting the data. The network was implemented over the course of 400 epochs due to the large dataset size.

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	11,264
dense_1 (Dense)	(None, 256)	131,328
dense_2 (Dense)	(None, 64)	16,448
dense_3 (Dense)	(None, 32)	2,080
dense_4 (Dense)	(None, 16)	528
dense_5 (Dense)	(None, 1)	17

Total params: 484,997 (1.85 MB)
Trainable params: 161,665 (631.50 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 323,332 (1.23 MB)

Figure 5: A summary of the **512-256-64-32-16-1** model architecture. This model served as an ideal candidate for overfitting the "Diabetes Health Indicators Dataset."

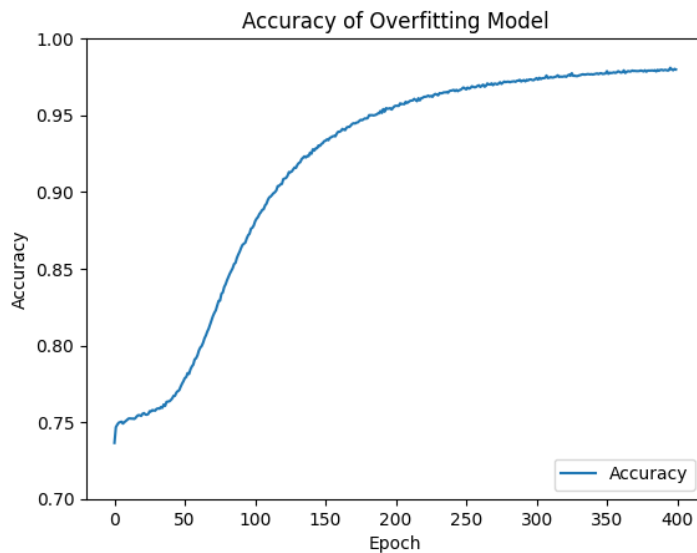


Figure 6: A graph illustrating the accuracy of the overfitting model over 400 epochs.

The model appeared to struggle with memorizing the dataset for the first 50 epochs. Its performance significantly improved between epochs 50 and 100 since Figure 6's chart encountered an upward concavity. The rate in which accuracy improves started decreasing at around 100 epochs, then continued to gradually diminish until it successfully completed all 400 epochs. Overfitting did not begin to occur until around the last 50 epochs of training. Since more than 70,000 samples exist in the data, it is rather challenging to overfit the data regardless of the neural network's configuration.

4 References

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