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# Stochastic Model for Risk Factors of Diabetes Patients

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**Abstract** Diabetes mellitus (DM) is a chronic condition that is potentially fatal. Over time, it can damage any organ of the body, leading to significant consequences such nephropathy, neurology, and retinopathy. The main objective of this article is to predict the BP and BMI of the female diabetic patients by using a stochastic model. At first, Biomedical characterizes and their statistical properties to all the study variables are described by TPM and Steady State. From the result of the TPM, most of the female patients have normal BP and they are at the level of obesity. The predicted results shows that the obese women will be in the high risk of developing diabetes, even if their BP is normal after 10 years from steady state.

***Keywords:*** *Markov chain, TPM, diabetes, BMI and HIV*

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## 1. Introduction

Diabetes is a chronic illness that alters the way our bodies convert food into energy. The majority of the food you consume is converted to sugar (also known as glucose) and released into your bloodstream. Patient’s pancreas releases insulin when the blood sugar levels rise. Insulin works as a key to allow blood sugar to enter cells and be used as energy. If they have diabetes, your body either does not produce enough insulin or does not utilise it as effectively as it should. Too much blood sugar persists in your bloodstream when there isn't enough insulin or when cells stop responding to insulin. This can lead to major health issues like heart disease, eyesight loss, and renal illness over time. Although there is no cure for diabetes, decreasing weight, eating healthy foods, and exercising can all help. Taking medication as needed, receiving diabetes self-management education and support, and keeping health-care appointments can all help to lessen the impact diabetes has on patient’s life.

Abebe et al., [1] estimated the commonness of diabetes mellitus (DM) and associated factors among HIV infected adults in northwest Ethiopia. They have also applied a multivariate logistic regression analysis and estimated the factors associated with diabetes mellitus. They showed that the overall prevalence of diabetes among HIV infected individual was 8%.

Belay et al., [2] estimated the pooled prevalence and associated factors of diabetes mellitus among adults in Ethiopia. They estimated the overall prevalence of diabetes mellitus among adults on Highly Active Anti-retroviral therapies (HAART) using a weighted inverse random effect model and also conducted sub-group analysis for evidence of heterogeneity. Fiseha & Belete [3] determined the prevalence of diabetes mellitus and its associated factors among human immunodeficiency virus-infected patients on anti-retroviral therapy in Northeast Ethiopia. They have demonstrated the necessity for routine diabetes screening among HIV-infected patients receiving ART. Woldu et al., [4] determined the prevalence of Cardiometabolic syndrome CMetS in PLWHA using the National Cholesterol Education Program (NCEP) and the International Diabetes Federation (IDF) tools. They used binary logistic regression to analyse the data. Fanta et al., [5] studied the magnitude of diabetes mellitus and risk factors among adult HIV patients exposed to HAART. In order to find factors that are independent predictors of diabetes mellitus, bivariate and multivariate logistic regressions were used. The results showed that exposure to Highly Active Anti-Retroviral Therapies (HAART) increased the prevalence of diabetes mellitus in PLWHIV, despite the fact that HAART improves quality of life, boosts immune system performance, and delays the onset of opportunistic infections. Han et al., [6] identified the prevalence and danger signs of new-onset diabetes in PLHIV in Asian environments. They utilised a Cox regression model stratified by location to determine the risk variables for diabetes, and the results showed that type 2 DM in Asians with HIV was linked to longer follow-up years, high blood pressure, obesity, and older age. Rajagopaul et al., [7]. Used univariate and multivariable binary logistic regression to evaluate odds ratios and relationships of interest. Their results show that, as HIV-positive people live longer and put on weight, it is imperative to prepare for the rising burden of NCDs. Cao et al., [8] employed DerSimonian-Laird random effects meta-analyses to determine the relationship between anemia prevalence and study characteristics, such as study design, median year of sampling, geographic region, World Bank Income level, and proportion of antiretroviral therapy (ART). Agezew et al., [9] have studied that how often ART failure is in adult HIV patients in North West Ethiopia who are also doing ART and what clinical factors predict it. And also utilised the bi-variable and multivariable Cox proportional hazard model. $P \leq 0.05$ was used to declare the connection. Ssentongo et al. [10], have examined the incidence of diabetes and risk variables among HIV patients receiving ART who are hospitalised to the ART clinic at Mulago National Referral Hospital. 200 HIV-positive individuals participated in the research. To evaluate variables connected to diabetes, they also used a multivariate logistic analysis. Sogbanmu et al., [11] examined the prevalence of diabetes mellitus of 335 newly diagnosed HIV-positive patients to identify the determinants of aberrant glycated haemoglobin by using logistic regression analysis. Ahmed et al., [12] assessed the prevalence and risk factors for TB in adult HIV-positive individuals with bivariate and multivariate Cox proportional hazards model.

## 2. Data Source

The secondary data is used to analyse the diabetes patients in India. It was collected from the Kaggle website. https://www.kaggle.com/datasets/mathchi/diabetes-data-set.

### 2.1. Details about Data

Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Indian heritage.

Number of instances: 768

Number of variables: 9

For each variable are all numeric- values. All the variables shown in below.

- **Pregnancies**: Number of times pregnant
- **Glucose**: Plasma glucose concentration 2 hours in an oral glucose tolerance test
- **Blood Pressure**: Diastolic blood pressure (mm Hg)
- **Skin Thickness**: Triceps skin fold thickness (mm)
- **Insulin**: 2-Hour serum insulin (mu U/ml)
- **BMI**: Body mass index (weight in kg/ (height in m) ^2)
- **Diabetes Pedigree Function**: Diabetes pedigree function
- **Age**: Age (years)
- **Outcome**: Class variable (0 or 1)

There are 9 variables we have. There is one dependent variable and the other 8 variables are independent. Outcome is the dependent variable, 0 means No diabetes and 1 means diabetes.

### 2.2. Missing Values Removal

Remove all the instances that have zero as worth. Data having zero as worth is not possible to calculate the accuracy result. Therefore, this instance is eliminated for the most valuable result. At the end there are 729 cases in the database.

### 2.3. Splitting of Data

The researcher clears the 9 variables into 4 variables data for this chapter purpose. They are age, blood pressure, BMI and outcome.

## 3. Methodology

### 3.1. Stochastic Process

The Stochastic process $\underline{X} = \{X(t), t \in T\}$ is a collection of random variables. That is, for each $t$ in the index set $T$, $X(t)$ is a random variable. We often interpret $t$ as time and call $X(t)$ the state of the process at time $t$. If the index set $T$ is a countable set, we call $\underline{X}$ a discrete – time stochastic process, and if $T$ is a continuum, we call it a continuous – time.

### 3.2. Transition Probability Matrix

The one-step transition probability matrix P of a Markov chain is given by

$$\begin{bmatrix} p_{0,0} & p_{0,1} & p_{0,2} & \cdots \\ p_{1,0} & p_{1,1} & p_{1,2} & \cdots \\ p_{2,0} & p_{2,1} & p_{2,2} & \cdots \\ p_{3,0} & p_{3,1} & p_{3,2} & \cdots \end{bmatrix}$$

i. we have indicated the possible states of the Markov chain to the eft of and above the matrix, in order to facilitate the comprehension of this transition matrix. The state to the left is the one in which the process is at time n, and the state above that in which the process will be at time $n+1$.

ii. Since the $p_{i,j}$ 's is (conditional) probabilities, we have

$$p_{i,j} \geq 0 \quad \forall i, j$$

Moreover, because the process must be in one and only one state at time $n+1$, we may write that

$$\sum_{j=0}^{\infty} p_{i,j} = 1 \quad \forall j$$

A matrix that possesses these two properties is said to be stochastic. The sum $\sum_{i=0}^{\infty} p_{i,j}$, for its part, may take any nonnegative value. If we also have

$$\sum_{i=0}^{\infty} p_{i,j} = 1 \quad \forall j$$

The matrix **P** is called doubly stochastic.

We now wish to generalize the transition matrix **P** by considering he case when the process moves from state $i$ to state $j$ in n steps. We then introduce the following notation.

The probability of moving from state I to state j in n steps (or transitions) is denoted by

$$p_{i,j}^{(n)} := P\left(X_{m+n}|X_m = i\right), \text{for } m,n,i,j \geq 0$$

From the $p_{i,j}^{(n)}$ we can construct the matrix $P^{(n)}$ of the transition probabilities in $n$ steps. This matrix and P have the same dimensions. Moreover, we find that we can obtain $P^{(n)}$ by raising the transition matrix **P** to the power $n$.

## 3.3. Markov Property

A Stochastic process $X(t)$ $(t = 0,1,2,\dots)$ with countable state space $I$ is said to beMarkov chain (M.C.) if for all states $i_0$ , $i_1$ , ... $i_{n-1}$ , $i, j, \in I, n > 0$,

$$P\left[X_{n+1} = j \mid X_{n-1} = i_{n-1}, \dots X_0 = i_0\right]$$
$$= P\left[X_{n+1} = j \mid X_n = i\right]$$

Then the sequence $\{X_n\}$ is said to possess Markov property.

## 3.4. Markov Chain

The Stochastic process $\{X_n , n = 0,1,2,\dots\}$ is called a Markov chain, if for $j, k, j_1, \dots ,j_{n-1} \in N$ (or any subset of $I$),

$$\Pr\left\{X_n = k \mid X_{n-1} = j, X_{n-2} = j_1, \dots, X_0 = j_{n-1}\right\}$$
$$= \Pr\left\{X_n = k \mid X_{n-1} = j\right\} = p_{jk} (say$$

The outcomes are called the states of the Markov chain; if $X_n$ has the outcome $j$ , $(i.e. X_n = j)$, the process is said to be at state j at n$^{th}$ trail. To a pair of states $(j, k)$ at the two successive trails $(say\ , nth\ and\ (n+1)\ st\ trails)$ there is an associated conditional probability $p_{jk}$ . It is the probability of transition from the state $j$ at n$^{th}$ trial to the state $k$ at $(n + 1)st$ trial. The transition probabilities $p_{jk}$ are basic to the study of the structure of the Markov chain.

The transition probability may or may not be independent of $n$. If the transition probability $p_{jk}$ is independent of $n$ , the Markov chain is said to be homogeneous (or to have stationary transition probabilities). If it is dependent on n, the chain is said to be non – homogenous. Here we shall confine to homogeneous chains. The transition probability $p_{jk}$ refers to the states $(j, k)$ at two successive trials (*say, n$^{th}$ and (n+1)$^{st}$ trial*); the transition is one – step and $p_{jk}$ is called one – step (or unit step) transition probability. In some general case, we concerned with the pair of states $(j, k)$ at two non – successive trails, say, state $j$ at the nth trail and state k at the (n+m)th trial. The corresponding transition probability is then called m – step transition probability and is denoted by $P_{jk}^{(m)}$ , $i.e.$

$$P_{jk}^{(m)} = \Pr\left\{X_{n+m} = k \mid X_n = j\right\}$$

## 3.5. Stationary Distribution

A Stationary probability distribution represents “equilibrium” of the Markov chain; that is, a probability distribution that remains fixed in time. For instance, if the chain is initially at a stationary probability distribution, $(0) = \pi$, the $p(n) = P^n \pi = \pi$ for all time $n$.

A stationary probability distribution of $DTMC$ with states {1, 2, . . . } is a nonnegative vector $\pi = (\pi_1, \pi_2, \dots)^{tr}$ that satisfies $P\pi = \pi$ and whose elements sum to one. That is,

$$\sum_{i=1}^{\infty} \pi_i = 1 .$$

This definition also applies to a finite Markov chain, where the vector $\pi = (\pi_1, \pi_2, \dots)^{tr}$ And $\sum_{i=1}^{N} \pi_i = 1$. In the finite case, $\pi$ is a right eigenvector of $P$ corresponding to the eigenvalue $\lambda = 1$, $P\pi = \lambda\pi$. There may be one or more than one linearly independent eigenvector corresponding to the eigenvalue $\lambda = 1$. If there is more than one nonnegative eigenvector, then the stationary probability distribution is not unique.

# 4. Results and Discussions

## 4.1. Data Source

The secondary data is used to analyse the diabetes patients in India. It was collected from the Kaggle website. https://www.kaggle.com/datasets/mathchi/diabetes-data-set. There are 4 variables which are age, BP, BMI and outcome related characteristics were observed from each patient at different occasion/time period record information about 729 diabetics patients are considered. The blood pressure and body mass index of the diabetics female patients classified into three states. They are state 1, state 2 and state 3.

## 4.2. Blood Pressure of the Patients

First we classify the blood pressure of the patients the 3 states are given below:

**Table 1. Division of 3 states**

| States | Interval | Name |
|---|---|---|
| State 1 | X<80 | Normal |
| State 2 | 80<X<90 | Prehypertension |
| State 3 | X>90 | Hypertension |

**Table 2. Transition count matrix for Blood Pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 443 | 80 | 42 |
| State 2 | 74 | 15 | 15 |
| State 3 | 48 | 9 | 2 |

**Table 3. Transition Probability Matrix for Blood Pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0.7840708 | 0.1415929 | 0.07433628 |
| State 2 | 0.7115385 | 0.1442307 | 0.14423077 |
| State 3 | 0.8135593 | 0.1525424 | 0.03389831 |

**Table 4. Steady state of Blood Pressure**

| Normal | Pre-hyper | Hyper |
|---|---|---|
| 0.776 | 0.143 | 0.081 |

Table 1 show that categories of the BP level of the patients. Table 2 was obtained 3×3 transition count matrix for 3 states. Table 3 shows that the probabilities of the BP level of patients form one state to another state. The estimation probability from state 1 and 2 to state 3 was 7.4% and 14%. The estimation of the transition probability from 1 and state 3 to state 2 was 14%, 15%. The estimation of the transition probability from 2 and state 3 to state 1 was 71.2% and 81.4%. The estimation of transition for staying the same states is 78%, 14% and 3%. From the table compared to the other state, the probability value from state 1, state 2 and state 3 to 1 are higher and also the probability value from state 1, state 2 to state 3 to 3 are low. Table 4 shows that after 10 years, the steady state of the normal, prehypertension, and hypertension will be 77.6%, 14.3%, and 8.1 % respectively. From this we predict that people with diabetes will have normal BP in the future as well.

## 4.3. BP with Diabetes Patients

**Table 5. Transition count matrix for patients with Blood pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 114 | 38 | 22 |
| State 2 | 39 | 5 | 14 |
| State 3 | 21 | 5 | 2 |

**Table 6. Transition Probability matrix for patients with Blood Pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0.6555 | 0.2183 | 0.1264 |
| State 2 | 0.8125 | 0.1042 | 0.0833 |
| State 3 | 0.75 | 0.1786 | 0.07143 |

**Table 7. Steady state probability of diabetic patients with BP:**

| Normal | Pre-hyper | Hyper |
|---|---|---|
| 0.696 | 0.192 | 0.112 |

Table 5 was obtained 3×3 transition count matrix for 3 states, this table shows that categories of the BP level of the female diabetic patients, there are 250 patients who affected by the diabetes. Table 6 shows that the probabilities of the BP level of patients form one state to another state. The estimation probability from state 1 and 2 to state 3 was 12.6% and 8.3%. The estimation of the transition probability from 1 and state 3 to state 2 was 21.8%, 17.9%. The estimation of the transition probability from 2 and state 3 to state 1 was 81.3% and 75%. The estimation of transition for staying the same states is 65.6%, 10.4% and 7.1%. From the table, compared to the other state, the probability value from state 1, state 2 and state 3 to 1 are higher and also the probability value from state 2 and state 3 to 3 are all low. Table 7 shows that after 10 years, the steady state of the normal, prehypertension, and hypertension will be 69.6%, 19.2%, and 11.2 % respectively. From this we predict that the patients will have normal BP in the future as well.

## 4.4. Blood Pressure without Diabetes Patients

**Table 8. Division of 3 state transition count matrix for Blood pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0 | 0 | 4 |
| State 2 | 1 | 13 | 83 |
| State 3 | 3 | 84 | 540 |

**Table 9. Transition probability matrix for Blood Pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0.813 | 0.123 | 0.064 |
| State 2 | 0.8 | 0.1 | 0.1 |
| State 3 | 0.903 | 0.0645 | 0.0322 |

**Table 10. Steady state of Blood Pressure:**

| Normal | Pre-hyper | Hyper |
|---|---|---|
| 0.818 | 0.117 | 0.065 |

Table 8 was obtained 3×3 transition count matrix for 3 states, this table shows that categories of the BP level of the female non diabetic patients, there are 494 patients who affected by the diabetes. Table 9 shows that the probabilities of the BP level of patients form one state to another state. The estimation probability from state 1 and 2 to state 3 was 6.4% and 10%. The estimation of the transition probability from 1 and state 3 to state 2 was 12.3%, 6.5%. The estimation of the transition probability from 2 and state 3 to state 1 was 80% and 90.3%. The estimation of transition for staying the same states is 81.3%, 10% and 3.2%. From the table compared to the other state, the probability value from state 1, state 2 and state 3 to 1 are higher and also the probability value from state 2 and state 3 to 3 are all low. Table 10 shows that after 10 years, the steady state of the normal, prehypertension, and hypertension will be 81.8%, 11.7%, and 6.5% respectively. From this we predict that non diabetic patients will have normal BP in the future as well.

## 4.5. BMI of the Patients

The body mass index of the diabetics female patients classified into three states. The classification of the BMI is given below:

**Table 11. Division of 3 states**

| States | Interval | Name |
|---|---|---|
| State 1 | X<18.5 | Underweight |
| State 2 | 18.5<X<25 | Normal |
| State 3 | X>25 | Obesity |

**Table 12. Division of 3 state transition count matrix for Blood pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 317 | 48 | 42 |
| State 2 | 45 | 6 | 5 |
| State 3 | 28 | 2 | 1 |

**Table 13. Transition probability matrix for Blood Pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0 | 0 | 1 |
| State 2 | 0.01 | 0.134 | 0.856 |
| State 3 | 0.004 | 0.134 | 0.8612 |

**Table 14. Steady state of Blood Pressure:**

| Underweight | Normal | Obesity |
|---|---|---|
| 0.006 | 0.133 | 0.861 |

Table 11 shows that categories of the BMI level of the patients. Table 12 was obtained 3×3 transition count matrix for 3 states. Table 13 shows that the probabilities of the BMI level of patients form one state to another state. The estimation probability from state 1 and 2 to state 3 was 100% and 85.6%. The estimation of the transition probability from 1 and state 3 to state 2 was 0%, 13.4%. The estimation of the transition probability from 2 and state 3 to state 1 was 10% and 4%. The estimation of transition for staying the same states is 0%, 13.4% and 86.1%. Zero indicated that the patient's blood pressure is not moving from the current level to the next level. From the table compared to the other state, the probability value from state 1, state 2 and state 3 to 3 are higher and also the probability value from state 1, state 3 to state 1 and from state 1 to 2 are all very low. Table 14 shows that after 10 years, the steady state of the Underweight, Normal, and Obesity will be 6%, 13.3%, and 86 % respectively. From this we predict that the patients will have obesity level of BMI in the future as well.

### 4.6. BMI without Diabetics

**Table 15. Division of 3 state transition count matrix for Blood pressure**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0 | 0 | 4 |
| State 2 | 1 | 16 | 73 |
| State 3 | 3 | 74 | 306 |

**Table 16. Transition probability matrix for BMI**

| States | State 1 | State 2 | State 3 |
|---|---|---|---|
| State 1 | 0 | 0 | 1 |
| State 2 | 0.011 | 0.178 | 0.811 |
| State 3 | 0.0078 | 0.193 | 0.799 |

**Table 17. Steady state of Blood Pressure after 10 years:**

| Underweight | Normal | Obesity |
|---|---|---|
| 0.008 | 0.189 | 0.803 |

Table 15 was obtained 3×3 transition count matrix for 3 states. Table 16 shows that the probabilities of the BMI level of patients form current state to next state. The estimation probability from state 1 and 2 to state 3 was 100% and 81.1%. The estimation of the transition probability from 1 and state 3 to state 2 was 0%, 19.3%. The estimation of the transition probability from 2 and state 3 to state 1 was 1.1% and 0.78%. The estimation of transition for staying the same states is 0%, 17.8% and 89.9%. Zero indicated that the patient's blood pressure is not moving from the current level to the next level. From the table compared to the other state, the probability value from state 1, state 2 and state 3 to 3 are higher and also the probability value from state 1, state 3 to state 1 and from state1 to 2 are all very. Table 17 shows that after 10 years, the steady state of the Underweight, Normal, and Obesity will be 0.8%, 18.9%, and 80.3 % respectively. From this we predict that the patients will have obesity level of BMI in the future as well.

## 5. Conclusion

According to this study, the majority of female patients have normal blood pressure are more prone to develop it in the future. The steady state shows that after 10 years, 78% of women with Normal BP are at risk of developing diabetics. People who do not currently have diabetes based on BP have a 77.6% chance of developing the disease in the future. From the transition probability matrix, Obesity patients is more prone to developing patients who are currently of normal weight. As a result, patients have a higher chance of developing diabetes in the future. The steady state shows that after 10 years, 86% of women with obesity are at risk of developing diabetics. People who do not currently have diabetes based on BMI have an 80.3% chance of developing the disease in the future. Also concluded, people with high or low blood pressure are not considered diabetic. Obesity, on the other hand, is mostly likely to lead to diabetes.


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