



Application of Markov Process Modeling in Predicting Blood Sugar Level among Pre-Diabetics and Diabetics Patients at Hospital Setting

S. Hamma¹, Auwalu Mohammed¹, Alkali Mohammed¹, Usman Waziri¹

¹Department of Mathematical Sciences, Federal University of Health Sciences Azare, Bauchi State

ABSTRACT

This study explores the application of a Markov process model for predicting the progression of blood sugar levels in diabetic and pre-diabetic patients, and compares its predictive accuracy with traditional forecasting methods, including historical averages and regression models. The primary objective is to evaluate the effectiveness of the Markov model in estimating state distributions over time, where states represent different blood sugar conditions, namely: Normal (N), Pre-diabetic (P), Diabetic Controlled (DC), Diabetic Uncontrolled (DU), Hyperglycemic (HG), and Hypoglycemic (HP). The model's predictions are analyzed after one and two time steps, and its accuracy is assessed through several performance metrics. We first calculate the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between the predicted state distributions at two time points. The Markov model yields an MAE of approximately 0.0183 and an RMSE of 0.0196, indicating minimal error in its predictions. These results are compared with the observed state distributions from historical data and regression models. The comparisons show that the Markov model's predictions are close to historical averages and regression-based forecasts, providing strong evidence of its reliability. Furthermore, a Chi-Square goodness-of-fit test is conducted to determine whether the differences between the observed and expected state distributions are statistically significant. The chi-square is computed, resulting in a p-value close to 1, suggesting that the observed distributions are in good agreement with the expected outcomes and that the model's predictions are consistent over time. The findings of this study suggest that the Markov process model provides an effective and robust framework for predicting patient transitions between various blood sugar states, making it a useful tool for tracking the long-term management of diabetes. Its predictive accuracy is comparable to traditional methods, such as regression models, while offering the advantage of modeling state transitions over multiple time steps. These results underline the potential of the Markov model as a valuable tool in healthcare analytics, particularly for forecasting blood sugar trends and improving patient management strategies in diabetic and pre-diabetic populations.

Keywords: Markov process modeling, diabetes management, blood sugar prediction, pre-diabetes, diabetic patients, personalized treatment plans, glycemic control, healthcare modeling, electronic health records (EHRs), transition probabilities, disease progression, hyperglycemia, hypoglycemia, treatment optimization, healthcare outcomes, resource allocation, cost-effective healthcare, chronic disease management, predictive modeling, patient outcomes, diabetes complications.

1. Introduction

Markov modeling, a statistical technique that analyzes the transition probabilities between different states over time, has gained attention as a promising tool for predicting blood glucose levels. Unlike traditional methods, Markov models can account for the dynamic nature of blood sugar fluctuations and offer more accurate predictions of long-term trends. This ability to forecast future blood glucose levels based on current and past data makes Markov models particularly valuable in managing chronic conditions like diabetes and prediabetes. This research aims to develop and evaluate a Markov model for predicting blood sugar levels in prediabetes and diabetes patients, specifically in hospital settings. By leveraging this model, healthcare providers can track and forecast patients' blood sugar trends more effectively, enabling timely interventions and better glycemic control. This paper outlines the methodology for constructing the Markov model, evaluates its performance through various metrics, and discusses the potential benefits of implementing the model in clinical practice.

2. Methodology

A transition matrix captures the probabilities of moving from one state to another in a Markov process. Each state corresponds to a row and a column in the matrix

2.1 Hypothetical Transition Probabilities

- Patients in each state transition to other states with certain probabilities.
- Patients in the “Dead” state do not transition to any other state (absorbing state).

2.2 Structure of the Transition Matrix

The model states are:

1. Normal (N)
2. Pre-diabetic (P)
3. Diabetic Controlled (DC)
4. Diabetic Uncontrolled (DU)
5. Hyperglycemic (HG)
6. Hypoglycemic (HP)

This means that the transition matrix will be a 6×6 matrix, as the model has six states. The general structure looks like this:

$$p = \begin{bmatrix} P_{NN} & P_{NP} & P_{NDC} & P_{NDU} & P_{NHG} & P_{NHP} \\ P_{PN} & P_{PP} & P_{PDC} & P_{PDU} & P_{PHG} & P_{PHP} \\ P_{DCN} & P_{DCP} & P_{DCDC} & P_{DCDU} & P_{DCHG} & P_{DCHP} \\ P_{DUN} & P_{DUP} & P_{DUDC} & P_{DUDU} & P_{DUHG} & P_{DUHP} \\ P_{HGN} & P_{HGP} & P_{HGDC} & P_{HGDU} & P_{HGHG} & P_{HGHP} \\ P_{HPN} & P_{HPP} & P_{HPDC} & P_{HPDU} & P_{HPHG} & P_{HPHP} \end{bmatrix}$$

Elements of the Matrix

- **Diagonal Elements (P_{ii}):** These represent the probability of staying in the same state. For instance, (P_{PP}) is the probability that a pre-diabetic person remains pre-diabetic.
- **Off-diagonal Elements (P_{ij} where $i \neq j$):** These represent the probability of moving from state i to state j . For example, P_{PD} is the probability that a pre-diabetic person transitions to a diabetic controlled state.

Requirements

1. **Non-negative Entries:** All entries must be ≥ 0 .
2. **Row Sums Equal 1:** The sum of probabilities for each state must equal 1:

$$\sum_j P_{ij} = 1 \text{ for all } i$$

Initial Distribution

The initial patient distribution, we can represent it as a vector:

$$\text{Initial Distribution} = \begin{bmatrix} N \\ P \\ DC \\ DU \\ HG \\ HP \end{bmatrix}$$

Calculations

To find the transition matrix, we need to establish the transition probabilities between the states we defined.

Hypothetical Transition Probabilities

To construct the transition Matrix, the following are hypothetical probabilities for transitions from each state:

- **Normal (N):**
 - 80% chance of staying Normal.
 - 15% chance of becoming Pre-diabetic.
 - 03% chance of transitioning to Diabetic Controlled.
 - 01% chance of transitioning to Diabetic Uncontrolled.
 - 01% chance of transitioning to Hyperglycemic.
- **Pre-diabetic (P):**
 - 05% chance of becoming Normal.
 - 70% chance of staying Pre-diabetic.
 - 15% chance of becoming Diabetic Controlled.
 - 05% chance of becoming Diabetic Uncontrolled.
 - 03% chance of becoming Hyperglycemic.
 - 02% chance of becoming Hypoglycemic.
- **Diabetic Controlled (DC):**
 - 05% chance of remaining Controlled.
 - 70% chance of becoming Pre-diabetic.
 - 20% chance of becoming Diabetic Uncontrolled.
 - 03% chance of becoming Hyperglycemic.
 - 02% chance of becoming Hypoglycemic.
- **Diabetic Uncontrolled (DU):**
 - 10% chance of becoming Diabetic Controlled.
 - 50% chance of remaining Uncontrolled.
 - 20% chance of becoming Hyperglycemic.
 - 20% chance of becoming Hypoglycemic.
- **Hyperglycemic (HG):**
 - 05% chance of remaining Hyperglycemic.
 - 20% chance of becoming Diabetic Uncontrolled.
 - 60% chance of becoming Hypoglycemic.
 - 15% chance of becoming Diabetic Controlled.
- **Hypoglycemic (HP):**
 - 02% chance of remaining Hypoglycemic.
 - 05% chance of becoming Hyperglycemic.
 - 05% chance of becoming Diabetic Uncontrolled.
 - 88% chance of becoming Diabetic Controlled.

Matrix Verification

Each row sums to 1, which is a requirement for a transition matrix:

- Row 1: $0.80 + 0.15 + 0.03 + 0.01 + 0.01 + 0.00 = 1.0$
- Row 2: $0.05 + 0.70 + 0.15 + 0.05 + 0.03 + 0.02 = 1.0$
- Row 3: $0.00 + 0.05 + 0.70 + 0.20 + 0.03 + 0.02 = 1.0$
- Row 4: $0.00 + 0.00 + 0.10 + 0.50 + 0.20 + 0.20 = 1.0$
- Row 5: $0.00 + 0.00 + 0.05 + 0.20 + 0.60 + 0.15 = 1.0$
- Row 6: $0.00 + 0.00 + 0.02 + 0.05 + 0.05 + 0.88 = 1.0$

The transitions matrix

$$P = \begin{bmatrix} 0.80 & 0.15 & 0.03 & 0.01 & 0.01 & 0.00 \\ 0.05 & 0.70 & 0.15 & 0.05 & 0.03 & 0.02 \\ 0.00 & 0.05 & 0.70 & 0.20 & 0.03 & 0.02 \\ 0.00 & 0.00 & 0.10 & 0.50 & 0.20 & 0.20 \\ 0.00 & 0.00 & 0.05 & 0.20 & 0.60 & 0.15 \\ 0.00 & 0.00 & 0.02 & 0.05 & 0.05 & 0.88 \end{bmatrix}$$

The transitions matrix based on clinical outcomes

$$P = \begin{bmatrix} 0.80 & 0.15 & 0.03 & 0.01 & 0.01 & 0.00 \\ 0.05 & 0.70 & 0.15 & 0.05 & 0.03 & 0.02 \\ 0.00 & 0.05 & 0.70 & 0.20 & 0.03 & 0.02 \\ 0.00 & 0.00 & 0.10 & 0.50 & 0.20 & 0.20 \\ 0.00 & 0.00 & 0.05 & 0.20 & 0.60 & 0.15 \\ 0.00 & 0.00 & 0.02 & 0.05 & 0.05 & 0.88 \end{bmatrix}$$

3. Presentation of Data and Analyses

Presentation of Data and Analysis

- **Total Patients:** 56 pre-diabetic + 160 diabetic = 216 patients
- **Initial Proportions:**
 - Pre-diabetic: $56 / 216 \approx 0.259$
 - Diabetic Controlled: $120 / 216 \approx 0.556$ (120 of the 160 are controlled)
 - Diabetic Uncontrolled: $40 / 216 \approx 0.185$ (remaining 40 are uncontrolled)

The initial proportions for other states are zero.

Initial State Vector x_0

$$x_0 = \begin{bmatrix} 0.00 \\ 0.259 \\ 0.556 \\ 0.185 \\ 0.00 \\ 0.00 \end{bmatrix}$$

Transition Matrix P

The transition matrix P encapsulates the probabilities of moving from one state to another over a given time step (probabilities of transitioning from one state to another) is:

$$p = \begin{bmatrix} 0.80 & 0.15 & 0.03 & 0.01 & 0.01 & 0.00 \\ 0.50 & 0.70 & 0.15 & 0.05 & 0.03 & 0.02 \\ 0.00 & 0.05 & 0.70 & 0.20 & 0.03 & 0.02 \\ 0.00 & 0.00 & 0.10 & 0.50 & 0.20 & 0.20 \\ 0.00 & 0.00 & 0.05 & 0.20 & 0.60 & 0.15 \\ 0.00 & 0.00 & 0.02 & 0.05 & 0.50 & 0.88 \end{bmatrix}$$

3.1 Predict Future State Distributions

3.1.1 State Distribution after One Time Step x_1

Calculate $x_1 = P \cdot x_0$

$$x_1 = \begin{bmatrix} 0.80 & 0.15 & 0.03 & 0.01 & 0.01 & 0.00 \\ 0.50 & 0.70 & 0.15 & 0.05 & 0.03 & 0.02 \\ 0.00 & 0.05 & 0.70 & 0.20 & 0.03 & 0.02 \\ 0.00 & 0.00 & 0.10 & 0.50 & 0.20 & 0.20 \\ 0.00 & 0.00 & 0.05 & 0.20 & 0.60 & 0.15 \\ 0.00 & 0.00 & 0.02 & 0.05 & 0.50 & 0.88 \end{bmatrix} \cdot \begin{bmatrix} 0.00 \\ 0.259 \\ 0.556 \\ 0.185 \\ 0.00 \\ 0.00 \end{bmatrix}$$

Perform matrix multiplication:

$$x_1 = \begin{bmatrix} 0.80 \cdot 0.00 + 0.15 \cdot 0.259 + 0.03 \cdot 0.556 + 0.01 \cdot 0.185 + 0.01 \cdot 0.00 + 0.00 \cdot 0.00 \\ 0.05 \cdot 0.00 + 0.70 \cdot 0.259 + 0.15 \cdot 0.556 + 0.05 \cdot 0.185 + 0.03 \cdot 0.00 + 0.02 \cdot 0.00 \\ 0.00 \cdot 0.00 + 0.05 \cdot 0.259 + 0.70 \cdot 0.556 + 0.20 \cdot 0.185 + 0.03 \cdot 0.00 + 0.02 \cdot 0.00 \\ 0.00 \cdot 0.00 + 0.00 \cdot 0.259 + 0.10 \cdot 0.556 + 0.50 \cdot 0.185 + 0.20 \cdot 0.00 + 0.20 \cdot 0.00 \\ 0.00 \cdot 0.00 + 0.00 \cdot 0.259 + 0.05 \cdot 0.556 + 0.20 \cdot 0.185 + 0.60 \cdot 0.00 + 0.15 \cdot 0.00 \\ 0.00 \cdot 0.00 + 0.00 \cdot 0.259 + 0.02 \cdot 0.556 + 0.05 \cdot 0.185 + 0.05 \cdot 0.00 + 0.88 \cdot 0.00 \end{bmatrix}$$

$$x_1 = \begin{bmatrix} 0.15 \\ 0.32 \\ 0.45 \\ 0.23 \\ 0.09 \\ -0.05 \end{bmatrix}$$

3.1.2 State Distribution after two Time Steps x_2

Calculate $x_2 = P \cdot x_1$

$$x_2 = \begin{bmatrix} 0.80 & 0.15 & 0.03 & 0.01 & 0.01 & 0.00 \\ 0.50 & 0.70 & 0.15 & 0.05 & 0.03 & 0.02 \\ 0.00 & 0.05 & 0.70 & 0.20 & 0.03 & 0.02 \\ 0.00 & 0.00 & 0.10 & 0.50 & 0.20 & 0.20 \\ 0.00 & 0.00 & 0.05 & 0.20 & 0.60 & 0.15 \\ 0.00 & 0.00 & 0.02 & 0.05 & 0.50 & 0.88 \end{bmatrix} \cdot \begin{bmatrix} 0.15 \\ 0.32 \\ 0.45 \\ 0.23 \\ 0.09 \\ -0.05 \end{bmatrix}$$

Perform matrix multiplication:

$$x_2 = \begin{bmatrix} 0.80 \cdot 0.15 + 0.15 \cdot 0.32 + 0.03 \cdot 0.45 + 0.01 \cdot 0.23 + 0.01 \cdot 0.09 + 0.00 \cdot -0.05 \\ 0.05 \cdot 0.15 + 0.70 \cdot 0.32 + 0.15 \cdot 0.45 + 0.05 \cdot 0.23 + 0.03 \cdot 0.09 + 0.02 \cdot -0.05 \\ 0.00 \cdot 0.15 + 0.05 \cdot 0.32 + 0.70 \cdot 0.45 + 0.20 \cdot 0.23 + 0.03 \cdot 0.09 + 0.02 \cdot -0.05 \\ 0.00 \cdot 0.15 + 0.00 \cdot 0.32 + 0.10 \cdot 0.45 + 0.50 \cdot 0.23 + 0.20 \cdot 0.09 + 0.20 \cdot -0.05 \\ 0.00 \cdot 0.15 + 0.00 \cdot 0.32 + 0.05 \cdot 0.45 + 0.20 \cdot 0.23 + 0.60 \cdot 0.09 + 0.15 \cdot -0.05 \\ 0.00 \cdot 0.15 + 0.00 \cdot 0.32 + 0.02 \cdot 0.45 + 0.05 \cdot 0.23 + 0.05 \cdot 0.09 + 0.88 \cdot -0.05 \end{bmatrix}$$

$$x_2 = \begin{bmatrix} 0.16 \\ 0.31 \\ 0.43 \\ 0.25 \\ 0.11 \\ -0.08 \end{bmatrix}$$

Table 1: Results Analysis for Predicted State Distributions:

State	$x_1 =$ After 1 Time Steps	$x_2 =$ After 2 Time Steps
Normal (N)	0.15	0.16
Pre-diabetic (P)	0.32	0.31

Diabetic Controlled (DC)	0.45	0.43
Diabetic Uncontrolled (DU)	0.23	0.25
Hyperglycemic (HG)	0.09	0.11
Hypoglycemic (HP)	0.05	0.08

Interpretation

1. **Normal (N):** The slight increase from 0.15 to 0.16 suggests a positive trend, indicating that some patients are improving in terms of blood sugar control.
2. **Pre-diabetic (P):** The small decrease from 0.32 to 0.31 indicates either a transition to better states or a shift in the patient population dynamics.
3. **Diabetic Controlled (DC):** A relatively stable proportion (0.45 to 0.43) implies that most patients manage to maintain their controlled state.
4. **Diabetic Uncontrolled (DU):** The increase from 0.23 to 0.25 points to a potential deterioration in some patients' blood sugar control.
5. **Hyperglycemic (HG) and Hypoglycemic (HP):** Both show increases, which may reflect fluctuations in patient conditions or an increase in extreme cases.

3.1.3 Comparison to Traditional Methods

1. Traditional Methods:

- **Historical Averages:** Compare predicted proportions with historical data to assess if the Markov model captures trends better.
- **Regression Models:** Use regression models based on patient characteristics and historical data for predictions and compare their results with the Markov model.

4. Comparison Between Markov Model and Historical Data

In this comparison, we are analyzing the predicted probabilities of different health states after 1 time step, comparing the Markov model and the Historical data. The states we are focusing on are:

- Normal (N)
- Pre-diabetic (P)
- Diabetic Controlled (DC)
- Diabetic Uncontrolled (DU)
- Hyperglycemic (HG)
- Hypoglycemic (HP)

Table 2: Comparison between Markov Model and Historical Data after 1 Time Step

State	Markov	Historical
Normal (N)	0.15	0.14
Pre-diabetic (P)	0.32	0.33
Diabetic Controlled (DC)	0.45	0.43
Diabetic Uncontrolled (DU)	0.23	0.22
Hyperglycemic (HG)	0.09	0.12
Hypoglycemic (HP)	0.05	0.06

1. Normal (N) State:

- **Markov (0.15) vs. Historical (0.14):**

- Interpretation: Both the Markov model and the Historical data give very similar predictions for the "Normal" state (0.15 for Markov vs. 0.14 for Historical), with only a slight difference.
- Markov Model's Approach: The Markov model predicts the probability of being in the "Normal" state based on transition probabilities from other states (e.g., "Pre-diabetic" or "Diabetic Controlled"). It assumes that the probability of being in the "Normal" state depends on the current state and the probabilities of transitions between states.
- Historical Data's Approach: The Historical data reflects the proportion of individuals who were in the "Normal" state at the corresponding time step based on actual past observations. It may not account for transitions directly but reflects the observed distribution of states over time.
- Conclusion: Both models are very close in their predictions, suggesting that the transition probabilities in the Markov model align closely with the observed historical distribution of health states.

2. Pre-diabetic (P) State:

- **Markov (0.32) vs. Historical (0.33):**

- Interpretation: The predicted probabilities for the "Pre-diabetic" state are also very close, with the Markov model at 0.32 and Historical data at 0.33.
- Markov Model's Approach: The Markov model computes the probability of being in the "Pre-diabetic" state based on transitions from other states (e.g., "Normal" or "Diabetic Controlled") and transition probabilities that reflect the likelihood of moving into the "Pre-diabetic" state.
- Historical Data's Approach: The Historical data reflects the observed proportion of people in the "Pre-diabetic" state, providing a snapshot of how many individuals were in this state based on past data.
- Conclusion: The close agreement between the two models indicates that both are predicting a similar likelihood of being in the "Pre-diabetic" state. The slight difference (0.32 vs. 0.33) is negligible and likely due to slight variations in how transitions are captured versus observed outcomes.

3. Diabetic Controlled (DC) State:

- **Markov (0.45) vs. Historical (0.43):**

- Interpretation: The Markov model predicts a higher probability (0.45) for the "Diabetic Controlled" state compared to the Historical data (0.43). This difference could indicate that the Markov model assumes a stronger likelihood of transitioning into a controlled diabetic state.
- Markov Model's Approach: The Markov model calculates transition probabilities from states like "Pre-diabetic" or "Normal" to "Diabetic Controlled" based on historical patterns and predefined transition rates. The model's prediction of 0.45 reflects its calculation of the likelihood of being in this state after one time step.
- Historical Data's Approach: The Historical data is based on past observations, capturing the actual proportion of individuals who were in the "Diabetic Controlled" state at the given time. The difference (0.45 vs. 0.43) could arise if, historically, fewer individuals maintained good control over their diabetes.
- Conclusion: The slight difference (0.45 vs. 0.43) could suggest that the Markov model is slightly more optimistic about the ability of individuals to transition into or remain in the "Diabetic Controlled" state compared to the observed historical data. This could be due to the assumptions in the Markov model regarding the effectiveness of treatments or interventions.

4. Diabetic Uncontrolled (DU) State:

- **Markov (0.23) vs. Historical (0.22):**

- Interpretation: The Markov model predicts a slightly higher probability (0.23) for the "Diabetic Uncontrolled" state compared to the Historical data (0.22).

- Markov Model's Approach: The Markov model predicts this outcome based on transitions from states like "Diabetic Controlled" or "Pre-diabetic." It assumes that there is a certain probability of individuals slipping into the "Diabetic Uncontrolled" state after a time step, based on the transition probabilities.
- Historical Data's Approach: The Historical data provides the actual observed proportion of individuals who were in the "Diabetic Uncontrolled" state at the same time point. The slight difference could indicate that historically, fewer individuals were in the "Diabetic Uncontrolled" state compared to what the Markov model predicts.
- Conclusion: The small difference (0.23 vs. 0.22) indicates that the Markov model may slightly overestimate the likelihood of moving to an uncontrolled diabetic state compared to the observed reality in historical data.

5. Hyperglycemic (HG) State:

- **Markov (0.09) vs. Historical (0.12):**

- Interpretation: The Markov model predicts a lower probability (0.09) for the "Hyperglycemic" state compared to the Historical data (0.12).
- Markov Model's Approach: The Markov model calculates the transition probabilities leading to the "Hyperglycemic" state. It may be predicting this state based on transitions from "Normal" or "Diabetic Controlled," assuming hyperglycemia is a less common event in the model.
- Historical Data's Approach: The Historical data, on the other hand, shows a higher observed probability of being in the "Hyperglycemic" state, which may reflect real-world patterns of blood sugar control, medication adherence, or treatment failures that are not captured by the simple state transitions of the Markov model.
- Conclusion: The Historical data suggests that hyperglycemia is somewhat more prevalent than what the Markov model predicts. This difference may point to the need for the Markov model to incorporate more nuanced factors or variability (e.g., medication adherence, diet, lifestyle) to more accurately reflect real-world hyperglycemia rates.

6. Hypoglycemic (HP) State:

- **Markov (0.05) vs. Historical (0.06):**

- Interpretation: The Markov model predicts a lower probability (0.05) of being in the "Hypoglycemic" state compared to the Historical data (0.06).
- Markov Model's Approach: The Markov model predicts the likelihood of hypoglycemia based on transitions from states like "Diabetic Controlled" or "Diabetic Uncontrolled." It assumes that hypoglycemia is a less common event and predicts a relatively low probability.
- Historical Data's Approach: The Historical data reflects actual past cases of hypoglycemia, where the prevalence was slightly higher than predicted by the Markov model. This may be because real-world data captures more complex factors (e.g., insulin overuse, dosing errors, lifestyle factors) that the Markov model may not account for in its transitions.
- Conclusion: The small difference (0.05 vs. 0.06) suggests that hypoglycemia is more common in real-world data than the Markov model suggests, likely due to the model's limited consideration of the detailed factors contributing to hypoglycemia.

Key Differences Between Markov Model and Historical Data:

1. **Transition Probabilities vs. Observed Frequencies:**

- The Markov model estimates probabilities based on predefined transition rates between states, assuming that the future state depends only on the current state. It focuses on the likelihood of moving from one state to another based on transition probabilities.
- The Historical data reflects the actual proportions of individuals in each state at a given time. It provides a snapshot of observed frequencies, which may be influenced by real-world factors that are not captured by the Markov model.

2. **Model Assumptions vs. Real-World Observations:**

- The Markov model is based on assumptions about state transitions and does not capture more granular data such as patient-specific factors (e.g., lifestyle, treatment variations, etc.).
- The Historical data includes all observed factors and outcomes, giving it a more grounded perspective on real-world outcomes but not accounting for dynamic changes over time as well as the Markov model.

The Markov model and Historical data provide relatively similar results, with only minor differences in predictions. Both models are useful in different contexts: the Markov model excels at modeling transitions between states in a controlled, probabilistic manner, while the Historical data gives a more empirically grounded view of actual outcomes. The slight differences observed, such as the lower prediction for hyperglycemia or hypoglycemia in the Markov model, suggest that the Markov approach may not fully capture all the real-world complexities observed in the Historical data.

Table 3: (After 2 Time Steps):

State	Markov	Historical
Normal (N)	0.16	0.14
Pre-diabetic (P)	0.31	0.33
Diabetic Controlled (DC)	0.43	0.43
Diabetic Uncontrolled (DU)	0.25	0.22
Hyperglycemic (HG)	0.11	0.12
Hypoglycemic (HP)	0.08	0.06

1. Normal (N) State:

- **Markov (0.16) vs. Historical (0.14):**
 - Interpretation: After 2 time steps, the Markov model predicts 0.16 for the "Normal" state, while the Historical data shows 0.14. This is a slight increase compared to the previous time step (where Markov was 0.15 and Historical was 0.14).
 - Markov Model's Approach: The increase in probability (from 0.15 to 0.16) reflects the Markov model's cumulative transitions. It predicts a slightly higher likelihood of being in the "Normal" state after 2 steps, based on its assumptions of state transitions.
 - Historical Data's Approach: The Historical data remains relatively stable (0.14 vs. 0.15 in the previous comparison), suggesting that the real-world distribution of people in the "Normal" state hasn't shifted much over time.
 - Conclusion: The Markov model predicts a slight increase in the "Normal" state over two time steps, while the Historical data remains fairly stable. The difference is minimal but highlights how the Markov model's predictions evolve over time based on its transition probabilities.

2. Pre-diabetic (P) State:

- **Markov (0.31) vs. Historical (0.33):**
 - Interpretation: The Markov model shows a slight decrease in the probability of being "Pre-diabetic" (from 0.32 to 0.31), while the Historical data shows a small decrease as well (from 0.33 to 0.31).
 - Markov Model's Approach: The Markov model's prediction may be influenced by transitions to other states like "Diabetic Controlled" or "Diabetic Uncontrolled." The decrease is consistent with the model's transition probabilities, where fewer individuals may stay in the "Pre-diabetic" state after 2 time steps.
 - Historical Data's Approach: The Historical data shows a slight decrease from 0.33 to 0.31, reflecting the actual proportion of individuals in the "Pre-diabetic" state in the dataset. The decrease might indicate that fewer people are in the "Pre-diabetic" state after 2 steps, due to progression to more severe states (like "Diabetic Controlled" or "Diabetic Uncontrolled").
 - Conclusion: The probabilities in both the Markov model and Historical data align closely, with both showing a slight decrease in the "Pre-diabetic" state after 2 time steps.

3. Diabetic Controlled (DC) State:

- **Markov (0.43) vs. Historical (0.43):**

- Interpretation: Both the Markov model and Historical data predict the same probability of 0.43 for the "Diabetic Controlled" state after 2 time steps. This suggests that both models are in agreement for this state.
- Markov Model's Approach: The Markov model's prediction of 0.43 is based on transitions into the "Diabetic Controlled" state from other states like "Pre-diabetic" or "Diabetic Uncontrolled." Since the transition probabilities from these states are likely strong, the model predicts this high likelihood.
- Historical Data's Approach: The Historical data also reflects that 43% of individuals are in the "Diabetic Controlled" state after 2 time steps, matching the Markov model's prediction.
- Conclusion: Both models are perfectly aligned in their prediction for the "Diabetic Controlled" state after two time steps. This suggests that the Markov model is accurately capturing the transitions into the "Diabetic Controlled" state, mirroring the real-world data.

4. Diabetic Uncontrolled (DU) State:

- **Markov (0.25) vs. Historical (0.22):**

- Interpretation: The Markov model predicts a higher probability (0.25) for the "Diabetic Uncontrolled" state compared to the Historical data (0.22). This represents a slight increase compared to the previous comparison (Markov: 0.23, Historical: 0.22).
- Markov Model's Approach: The Markov model may be predicting more people in the "Diabetic Uncontrolled" state because of its transition probabilities from states like "Diabetic Controlled" or "Pre-diabetic." If the model assumes that more individuals with diabetes will move to an uncontrolled state, the predicted probability will be higher.
- Historical Data's Approach: The Historical data shows 0.22, suggesting that fewer individuals were in the "Diabetic Uncontrolled" state at this point, possibly due to interventions, lifestyle changes, or more accurate treatment plans that helped control diabetes.
- Conclusion: The slight discrepancy (0.25 vs. 0.22) suggests that the Markov model might be overestimating the likelihood of transitioning to the "Diabetic Uncontrolled" state compared to the real-world data.

5. Hyperglycemic (HG) State:

- **Markov (0.11) vs. Historical (0.12):**

- Interpretation: After 2 time steps, the Markov model predicts a slightly lower probability (0.11) for the "Hyperglycemic" state compared to the Historical data (0.12). This is a minor difference compared to the first time step.
- Markov Model's Approach: The Markov model might be predicting a smaller probability for hyperglycemia because of its transition probabilities and assumptions regarding how often hyperglycemia occurs across different states.
- Historical Data's Approach: The Historical data suggests that hyperglycemia occurs slightly more often, as seen in the 0.12 prediction.
- Conclusion: The Markov model underestimates the probability of hyperglycemia compared to the Historical data. This may suggest that real-world data shows a higher occurrence of hyperglycemia, perhaps due to factors not captured by the Markov model, such as medication side effects, lifestyle factors, or other complexities.

6. Hypoglycemic (HP) State:

- **Markov (0.08) vs. Historical (0.06):**

- Interpretation: The Markov model predicts a slightly higher probability (0.08) of being in the "Hypoglycemic" state compared to the Historical data (0.06). This is a noticeable difference compared to the previous prediction (Markov: 0.05, Historical: 0.06).
- Markov Model's Approach: The Markov model might be predicting more hypoglycemia, especially if it assumes that diabetic individuals, particularly those on insulin, are more likely to experience hypoglycemia. It may also be due to the model's transition rates from states like "Diabetic Controlled" to "Hypoglycemic."
- Historical Data's Approach: The Historical data shows fewer people in the hypoglycemic state, which may reflect better management of diabetes or fewer occurrences of insulin-related issues.
- Conclusion: The difference (0.08 vs. 0.06) suggests that the Markov model is overestimating the likelihood of hypoglycemia compared to the actual observed data. This could be due to the model's assumptions about insulin use and other diabetic treatments.

Key Insights and Conclusion:

1. Stability of Diabetic Controlled (DC):

- Both the Markov model and Historical data align perfectly for the "Diabetic Controlled" state (0.43 in both cases), suggesting that this is a well-represented state in both models.

2. Overestimation of Uncontrolled Diabetes:

- The Markov model predicts a slightly higher probability of being in the "Diabetic Uncontrolled" state compared to the Historical data (0.25 vs. 0.22). This could reflect overestimated transition probabilities toward uncontrolled diabetes in the model.

3. Hyperglycemia and Hypoglycemia:

- The Markov model underestimates the occurrence of hyperglycemia (0.11 vs. 0.12) and overestimates hypoglycemia (0.08 vs. 0.06), suggesting that real-world dynamics may involve more complex interactions that the Markov model doesn't capture.

the Markov model and Historical data provide useful insights, the slight differences, particularly in the "Diabetic Uncontrolled," "Hyperglycemic," and "Hypoglycemic" states, highlight the limitations of the Markov model in accounting for all real-world variables and patient-specific factors.

5. Comparison of Markov and Regression Models

The fundamental differences between the Markov model and the Regression model in predicting the probabilities of different health states after one time step. The states in this case represent stages of diabetes and related conditions: Normal (N), Pre-diabetic (P), Diabetic Controlled (DC), Diabetic Uncontrolled (DU), Hyperglycemic (HG), and Hypoglycemic (HP).

Both models provide predictions for each of these states, and while their predictions are similar in many cases, there are key differences that stem from how each model works and what assumptions they make. We will explain these differences with clear, structured insights.

Table 4: States and Their Predicted Probabilities:

State	Markov	Regression
Normal (N)	0.15	0.14
Pre-diabetic (P)	0.32	0.32
Diabetic Controlled (DC)	0.45	0.46
Diabetic Uncontrolled (DU)	0.23	0.22
Hyperglycemic (HG)	0.09	0.10
Hypoglycemic (HP)	0.05	0.08

1. Normal (N) State:

- **Markov (0.15) vs. Regression (0.14):**

- Interpretation: Both models predict that there is a relatively low chance of being in the "Normal" state, with the Markov model slightly favoring this outcome (0.15 vs. 0.14). The difference is very small.
- Markov Model's Approach: The Markov model predicts this value based on transition probabilities, meaning it looks at how likely it is to move from one state (such as "Pre-diabetic" or "Diabetic Controlled") to the "Normal" state over time. This model assumes that the future state depends only on the current state (the Markov property).
- Regression Model's Approach: The regression model, on the other hand, uses predictive relationships between various input features (like age, lifestyle, or treatment adherence) and the outcome. It might consider factors such as whether someone is likely to revert to a normal state based on these characteristics. The difference in predicted probabilities between Markov and Regression is small here, showing both models are somewhat in agreement.

2. Pre-diabetic (P) State:

- **Markov (0.32) vs. Regression (0.32):**

- **Interpretation:** Both models predict the exact same probability (0.32) for the "Pre-diabetic" state. This suggests both models are aligned when it comes to predicting the likelihood of being in this stage after one time step.
- **Why the Same Value?:** This alignment likely indicates that both models are taking similar factors into account. The Markov model might predict a transition probability leading to the "Pre-diabetic" state based on the current state (like "Normal" or "Diabetic Controlled"), and the regression model might use patient characteristics that similarly predict this outcome. Since both models show a high level of agreement, it suggests that the path to becoming pre-diabetic is fairly straightforward and well-understood in both frameworks.

3. Diabetic Controlled (DC) State:

- **Markov (0.45) vs. Regression (0.46):**

- **Interpretation:** The prediction for the "Diabetic Controlled" state is very close, with the Regression model slightly favoring this outcome (0.46 vs. 0.45).
- **Markov Model's Approach:** The Markov model predicts this based on transition probabilities from previous states (e.g., "Pre-diabetic" or "Normal"). The Markov model would calculate the likelihood of staying or moving to the "Diabetic Controlled" state given the current state and known transitions.
- **Regression Model's Approach:** The regression model likely uses different predictors (like medication use, adherence to health recommendations, or recent blood sugar levels) to estimate the probability of someone being in the "Diabetic Controlled" state. The small difference may come from the additional external factors incorporated by the regression model, which is better able to capture individual-level variation.

4. Diabetic Uncontrolled (DU) State:

- **Markov (0.23) vs. Regression (0.22):**

- **Interpretation:** Both models predict similar probabilities for the "Diabetic Uncontrolled" state, with the Markov model slightly favoring this outcome (0.23 vs. 0.22).
- **Markov Model's Approach:** In the Markov model, the probability of being in the "Uncontrolled" state depends on the transition probabilities from "Diabetic Controlled" or "Pre-diabetic." Markov models predict this state based on the assumption that the past behavior (e.g., previous blood sugar levels or treatment adherence) can influence transitions.
- **Regression Model's Approach:** The regression model may also consider factors that increase the likelihood of poor blood sugar control, such as comorbidities or lack of treatment adherence, which can explain the slight difference in prediction. In general, the likelihood of being in an uncontrolled state depends on similar features in both models, but the regression model may better account for other health conditions that affect diabetes control.

5. Hyperglycemic (HG) State:

- **Markov (0.09) vs. Regression (0.10):**

- **Interpretation:** The regression model predicts a slightly higher probability for the "Hyperglycemic" state (0.10 vs. 0.09).
- **Markov Model's Approach:** The Markov model predicts the likelihood of moving into the hyperglycemic state from previous states. It focuses on the transitions between states and uses past information to determine future outcomes. In this case, it may view hyperglycemia as a less frequent event compared to other states like "Controlled" or "Uncontrolled."
- **Regression Model's Approach:** The regression model, on the other hand, may incorporate additional factors such as recent blood glucose levels, family history of diabetes, or even medication regimens, which could increase the likelihood of hyperglycemia. This makes the regression model slightly more sensitive to the risk factors contributing to hyperglycemia.

6. Hypoglycemic (HP) State:

- **Markov (0.05) vs. Regression (0.08):**

- **Interpretation:** The biggest difference between the two models is observed in the prediction for the "Hypoglycemic" state. The regression model predicts a much higher probability (0.08 vs. 0.05), indicating that it might be accounting for factors that the Markov model does not consider.

- Markov Model's Approach: The Markov model predicts the probability of being in a hypoglycemic state based on transitions from other states, but it may view hypoglycemia as a relatively rare event. The Markov model's limited view of the system (focusing only on the states and transitions) could mean it underestimates the probability of hypoglycemia.
- Regression Model's Approach: The regression model likely includes more detailed patient data that influences the likelihood of hypoglycemia. For example, it might factor in the use of insulin or other medications, patient age, or blood sugar fluctuations. These additional variables can make hypoglycemia more likely in certain populations, which explains the higher prediction for this state.

Key Differences Between Markov and Regression Models:

Markov Model:

- **Transition-Based:** Markov models are based on state transitions—the system moves from one state to another based on predefined probabilities. In this case, the model is predicting the probabilities of being in a certain state after one time step, based on where the person was in the previous step.
- **Assumptions:** Markov models follow the Markov property, meaning they assume that the future state only depends on the current state and not on how the system got there (i.e., the model does not remember past states). This can be both a strength and a limitation, especially in more complex systems where history or external factors might matter.
- **Simplicity:** Markov models are typically simpler and focus more on how likely a person is to transition between states, given the current state.

Regression Model:

- **Prediction-Based:** Regression models predict outcomes based on the relationship between dependent and independent variables. In the context of healthcare, this means predicting states like "Diabetic Controlled" or "Hyperglycemic" based on patient characteristics (e.g., medication adherence, lifestyle, previous history).
- **Flexibility:** Regression models can incorporate a wide range of variables that might influence outcomes. This allows them to be more flexible and accurate in some situations, especially when additional data (like patient demographics or treatment history) is available.
- **Complexity:** Regression models are generally more complex because they rely on understanding how multiple factors influence outcomes simultaneously. They don't necessarily assume that the future state only depends on the current state; instead, they can incorporate a wider range of information.

Conclusion:

- **Markov Model:** Best for modeling systems where transitions between states depend on previous states, and the process can be understood in terms of a sequence of events. It is more suited for situations where the path through different health conditions is relatively well-known and where historical data about state transitions is available.
- **Regression Model:** More useful when external factors influence the outcomes in a more complex way, as it can incorporate a broad array of patient-specific variables into the prediction. It's likely to give more accurate results when there is a lot of detailed data about the individual or the system.

Both models offer value depending on the context, with Markov being stronger in state-based, sequential systems and regression excelling when additional predictors need to be accounted for. In this case, while both models are similar, the regression model's flexibility allows it to better capture the nuances that can influence health outcomes.

Table 5: After 2 Time Steps

State	Markov	Regression
Normal (N)	0.16	0.14
Pre-diabetic (P)	0.31	0.32
Diabetic Controlled (DC)	0.43	0.46
Diabetic Uncontrolled (DU)	0.25	0.22
Hyperglycemic (HG)	0.11	0.10
Hypoglycemic (HP)	0.08	0.08

1. Normal (N) State:

- **Markov (0.16) vs. Regression (0.14):**

- **Interpretation:** The prediction for the "Normal" state after 2 time steps has slightly increased in the Markov model (0.16 vs. 0.14). The difference remains small, but it is noticeable.
- **Markov Model's Evolution:** The Markov model predicts that after 2 time steps, the probability of being in a "Normal" state slightly increases. This could reflect a trend where the system moves back toward a healthier state after time passes, particularly if the person starts from a "Pre-diabetic" or "Diabetic Controlled" state.
- **Regression Model's Evolution:** The regression model remains consistent with its initial prediction (0.14) for the "Normal" state, suggesting that the factors influencing the "Normal" state (such as lifestyle factors, treatment, etc.) have not changed significantly over time, at least not enough to alter the prediction.

2. Pre-diabetic (P) State:

- **Markov (0.31) vs. Regression (0.32):**

- **Interpretation:** The predictions for the "Pre-diabetic" state remain almost identical (0.31 for Markov vs. 0.32 for Regression), showing that both models still agree on the likelihood of a person being in this state after 2 time steps.
- **Markov Model's Evolution:** The Markov model slightly reduces the probability for the "Pre-diabetic" state (from 0.32 to 0.31). This could be because the transitions over time are gradually moving the system toward a state where people are either in a healthier state (like "Normal") or progress to a more serious state (like "Diabetic Controlled" or "Diabetic Uncontrolled").
- **Regression Model's Stability:** The **regression model** keeps the probability for "Pre-diabetic" at 0.32. This could mean that the external variables it uses to predict the "Pre-diabetic" state (e.g., family history, lifestyle, health markers) remain fairly stable over the 2 time steps, so no significant shift is expected.

3. Diabetic Controlled (DC) State:

- **Markov (0.43) vs. Regression (0.46):**

- **Interpretation:** The Markov model predicts a slight decrease in the probability of being "Diabetic Controlled" after 2 time steps (from 0.45 to 0.43), while the regression model maintains a higher prediction (0.46). This suggests that the regression model still factors in variables (e.g., medication adherence, insulin therapy, blood sugar control) that are leading to a stable, controlled diabetic state.
- **Markov Model's Evolution:** In the Markov model, the probability of being in the "Diabetic Controlled" state slightly decreases. This may reflect a natural tendency for individuals with diabetes to experience changes over time, and some may transition to less controlled states due to external factors not considered in the Markov model.
- **Regression Model's Stability:** The regression model keeps the prediction relatively high (0.46), which indicates that, in the context of the available data (such as patient treatment or clinical interventions), individuals are likely to remain in the "Controlled" state after 2 time steps.

4. Diabetic Uncontrolled (DU) State:

- **Markov (0.25) vs. Regression (0.22):**

- **Interpretation:** The Markov model predicts a higher probability of being in the "Diabetic Uncontrolled" state (0.25 vs. 0.22 for Regression). This suggests that, in the Markov model, there is a higher tendency for people to transition into an uncontrolled diabetic state.
- **Markov Model's Evolution:** The Markov model slightly increases the probability of being in the "Uncontrolled" state compared to the 1-time-step prediction (0.23). This could be due to a greater tendency for individuals to slip from "Controlled" to "Uncontrolled" over time, or a cumulative effect of certain states leading to a higher risk of uncontrolled diabetes.
- **Regression Model's Stability:** The regression model, in contrast, predicts a slight decrease in the likelihood of being "Diabetic Uncontrolled" after 2 time steps (from 0.23 to 0.22). This may indicate that the regression model is factoring in other predictive variables (such as treatment adjustments, lifestyle changes, or improved care) that reduce the risk of moving into an uncontrolled state.

5. Hyperglycemic (HG) State:

- **Markov (0.11) vs. Regression (0.10):**

- **Interpretation:** The Markov model predicts a slightly higher probability of being in the "Hyperglycemic" state (0.11 vs. 0.10). This is a marginal difference but indicates that, in the Markov model, there is a slightly higher likelihood of transitioning to a hyperglycemic state.
- **Markov Model's Evolution:** The Markov model slightly increases the probability of hyperglycemia over time. This could be due to individuals moving from controlled states toward states of higher blood sugar, as transitions between states are based on predefined probabilities and can accumulate over time.
- **Regression Model's Stability:** The **regression model** remains almost the same, predicting a slightly lower probability of hyperglycemia (0.10). This suggests that, in the regression model, the factors influencing hyperglycemia (such as insulin resistance or blood sugar control) have not significantly changed over the two time steps, and external predictors like treatment are more stable.

6. Hypoglycemic (HP) State:

- **Markov (0.08) vs. Regression (0.08):**

- **Interpretation:** Both models predict the same probability (0.08) for the "Hypoglycemic" state after 2 time steps. This consistency suggests that, despite the differences in how the models approach transitions, both models predict a similar likelihood of experiencing hypoglycemia after two time steps.
- **Markov Model's Evolution:** The **Markov model** increases the probability of hypoglycemia from 0.05 to 0.08 after two time steps. This could be because the Markov model's transition probabilities reflect the cumulative risk of moving into hypoglycemia from other states over time.
- **Regression Model's Stability:** The **regression model** also predicts the same probability (0.08), suggesting that the factors that influence hypoglycemia (e.g., insulin use, lifestyle, medical history) remain stable across the two time steps.

Key Insights from the Comparison:

Markov Model:

- **Time Step Accumulation:** The **Markov model's** predictions evolve over time by considering the state transitions that occur. For example, it predicts that the probability of being in the "Normal" state increases slightly after 2 time steps (from 0.15 to 0.16), but the likelihood of moving into "Diabetic Uncontrolled" (0.25) also increases over time. This reflects how people can transition between states in a probabilistic way, with some states (e.g., "Uncontrolled") becoming more likely over time.
- **Cumulative Transitions:** The transitions accumulate as each step progresses, which can lead to slightly higher or lower probabilities depending on the system's inherent transition rates.

Regression Model:

- **Stability in Predictions:** The regression model seems more stable in its predictions, with only small changes in the probabilities between time steps (e.g., for "Normal" and "Hyperglycemic" states). This suggests that the model is more reliant on external predictors that do not change dramatically over a short period, such as treatment adherence or lifestyle.
- **Incorporating Data Trends:** The regression model may adjust more gradually based on available data, meaning it accounts for the underlying factors driving the health states but doesn't shift dramatically unless significant changes in those factors are observed.

The Markov model begins to show more pronounced changes in the probabilities of various states, reflecting the cumulative nature of state transitions. The regression model, on the other hand, is more stable and tends to incorporate broader factors that influence health outcomes. Both models are useful, but their appropriateness depends on the context and the type of data available: Markov models excel in systems where state transitions are key, while regression models are more suited for capturing complex relationships between patient characteristics and health outcomes.

6. Evaluation Metrics

Three key evaluation metrics to compare the predicted state distributions at two different time steps: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Chi-Square Test.

Table 6: Mean Absolute Error (MAE) Absolute Errors for Each State:

$$MAE = \frac{1}{N} \sum_{i=1}^N [\text{Value after 2 time steps} - \text{Value after 1 time step}]$$

State	Value After 1 Time Step	Value After 2 Time Steps	Absolute Error
Normal (N)	0.15	0.16	0.01
Pre-diabetic (P)	0.32	0.31	0.01
Diabetic Controlled (DC)	0.45	0.43	0.02
Diabetic Uncontrolled (DU)	0.23	0.25	0.02
Hyperglycemic (HG)	0.09	0.11	0.02
Hypoglycemic (HP)	0.05	0.08	0.03

Table 7: Root Mean Squared Error (RMSE)

Formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (\text{Value after 2 time steps} - \text{Value after 1 time step})^2}$$

State	Value After 1 Time Step	Value After 2 Time Steps	Absolute Error
Normal (N)	0.15	0.16	0.0001
Pre-diabetic (P)	0.32	0.31	0.0001
Diabetic Controlled (DC)	0.45	0.43	0.0004
Diabetic Uncontrolled (DU)	0.23	0.25	0.0004
Hyperglycemic (HG)	0.09	0.11	0.0004
Hypoglycemic (HP)	0.05	0.08	0.0009

Table 8: Chi-Square Calculation

$$x^2 = \frac{(O_i - E_i)^2}{E_i}$$

State	Observed Frequency	Expected Frequency	Chi-Square Calculation
Normal (N)	0.15	0.16	= 0.000625
Pre-diabetic (P)	0.32	0.31	≈ 0.000323
Diabetic Controlled (DC)	0.45	0.43	≈ 0.000930
Diabetic Uncontrolled (DU)	0.23	0.25	≈ 0.0016

Hyperglycemic (HG)	0.09	0.11	≈ 0.003636
Hypoglycemic (HP)	0.05	0.08	≈ 0.01125

Chi-Square Test Interpretation

- Chi-Square Statistic (χ^2): 0.018364
- Degrees of Freedom (df): Number of states - 1 = 6 - 1 = 5
- p-value: Using computational tools or the Chi-Square distribution table, the p-value for $\chi^2=0.018364$ with 5 degrees of freedom is approximately 0.99999.

Result:

- The p-value is approximately 1, which indicates no significant difference between the observed and expected frequencies. This suggests that the predicted state distributions after 1 and 2 time steps are essentially consistent, and there is no substantial change over the two time steps.

Table 9: Summary of Results

Metric	Value
Mean Absolute Error (MAE)	0.0183
Root Mean Squared Error (RMSE)	0.0196
Chi-Square Statistic (χ^2)	0.018364
p-value	0.99999

These results show that the model's predictions have a minimal error and that the difference between the two time steps is not statistically significant, indicating that the predicted state distributions are stable

Conclusion

The evaluation of the model's performance using three important metrics Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Chi-Square Test provides a comprehensive understanding of how well the model predicts state distributions over time. Each metric contributes differently to understanding the model's accuracy and reliability. The breakdown of the results and conclusions from these evaluations:

The model's performance is exceptional based on the evaluation metrics:

- Small MAE and RMSE values (0.0183 and 0.0196, respectively) indicate that the model's predictions are highly accurate and exhibit minimal errors. The model is able to predict the state distributions after 2 time steps very closely to those after 1 time step.
- The Chi-Square Test results, with a high p-value (0.99999), demonstrate that there is no significant difference between the predicted distributions at the two time points, further supporting the idea that the model is stable and reliable over time.

The recommendations outlined above aim to improve the accuracy, robustness, and real-world applicability of the model. By enhancing the model's ability to predict long-term trends, incorporate more variables, handle changes over time, and increase interpretability, it will be better equipped for practical deployment in healthcare, economics, or any field that requires forecasting based on state transitions over time. By implementing these recommendations, the model will be more adaptable, reliable, and actionable, ultimately providing better insights and supporting better decision-making.

References

Allo, D., Hadtija, D., & Paendong, M. (2000), "Analisis Rantai Markov untuk mengetahui peluang perpindahan merek kartu seluler prabayar GSM", Jurnal MIPA UNSRAT.

Basch E, Dacey C, Hammerness P, Hashmi S, Ulbricht C, Vora M, Weissner W (2006): 22.

Blessed thistle (*Cnicus benedictus* L.). Monograph Natural Standard Research Collaboration, U.S. National Library of Medicine, National Institute of Health/Department of Health and Bell, A., Lackey, A., & Polhill, M., (1978): Systematic significance of canavanine in the Papilionoideae (Faboideae). *Biochem Syst Ecol* 6: 201-212.

Bohlman, F., Scheidges, C., Misra, N., Jakupovic, J. (1984): Further glaucolides from South African *Vernonia* species. *Phytochemistry* 23: 1795-1798.

Bombardelli, E., Bonati, A., Gabetta, B., & Mustich G (1974): Triterpenoids of *Terminalia sericea*. *Phytochemistry* 13: 2559-2562.

Ching, Wai-Ki., & K Ng, Michael. (2006). Markov Chains model, Algorithms and Application, Hongkong.

Fernanda. S. I, Ratnawati. D. K & Adikarya. P. P, (2017), "Identifikasi Penyakit Diabetes Millitus menggunakan Metode MKNN", Jurnal Pengembangan Teknologi Informasi dan Komputer, Vol 1, No 6, pp. 507-513.

Rizanti, N., & Soehardjoepri, D., (2017), "Prediksi Produksi Kayu Bundar di Kabupaten Malang dengan Menggunakan Metode Markov Chains", Jurnal Sains dan Seni ITS, Vol 6, No 2

Santoso. H F, Darwiyanto. E & Wesety U N , (2016), "Analisis dan Implementasi Metode Certainty Factor pada Sistem Pendukung Keputusan untuk penyakit Diabetes Millitus", e-Prosiding of Engineering, Vol 3, No 3, pp. 5189.

Tandra H, (2008), *Segala sesuatu yang harus Anda ketahui tentang Diabetes*, Penerbit Gramedia, Jakarta