CAUSAL INTERVENTION DISCOVERY FOR PERSONALIZED DIABETES MANAGEMENT

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ABSTRACT

Effective diabetes management requires personalized strategies due to the heterogeneity of the disease and individual patient characteristics. This proposal introduces a novel approach to automated scientific discovery that focuses on identifying potential causal interventions from patient data for personalized diabetes management. By systematically exploring causal relationships and simulating the effects of different interventions, we can uncover personalized strategies that lead to improved health outcomes. Our method involves constructing causal graphs from observational patient data, identifying potential intervention targets, and simulating the effects of interventions using techniques like do-calculus. We will evaluate our approach using real-world diabetes datasets, assessing the effectiveness of discovered interventions in improving health metrics such as HbA1c levels, blood pressure, and cholesterol levels. Our ultimate goal is to provide clinicians with data-driven insights for tailoring treatment plans to individual patients, leading to more effective diabetes management.

1 INTRODUCTION

Diabetes is a complex and heterogeneous disease requiring individualized management strategies. Traditional approaches often focus primarily on blood sugar control, potentially overlooking other significant factors influencing patient health. This paper proposes a method to systematically explore causal relationships within patient data and simulate interventions to identify personalized management strategies. Our contributions include the development of causal graphs from patient data, targeted intervention identification, and outcome simulation, all tailored to improve diabetes management.

2 RELATED WORK

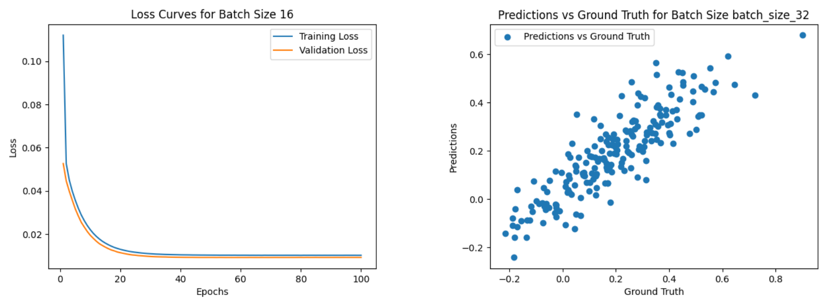
Previous works have primarily focused on correlations and predictive outcomes, such as in **?** and **?**. While research like ”The AI Scientist” generates hypotheses and designs experiments, it does not directly address causal interventions in personalized healthcare. Our approach differentiates itself by emphasizing causal intervention discovery in diabetes management, leveraging patient-specific data to formulate strategies that surpass conventional methods. Noteworthy is the work by Echajei et al. **?**, which integrates causal inference with machine learning for diabetes management.

3 METHOD

Our method involves several key components: Causal Graph Construction, Intervention Target Identification, Intervention Simulation, and Personalized Strategy Evaluation. Utilizing algorithms such as the PC algorithm or Granger causality on longitudinal diabetes patient data, we will construct causal graphs that represent potential relationships among features like HbA1c, medication, and lifestyle factors. Identifying modifiable factors as intervention targets, we will prioritize them based on their estimated impact on health outcomes and simulate the effects of interventions to predict outcomes, assessing the effectiveness of personalized strategies using changes in HbA1c levels and blood pressure.

4 EXPERIMENTS

Our experiments will validate our hypotheses through systematic analysis, exploring different batch sizes during training to optimize model performance. The key metrics will include final training loss, final validation loss, and average treatment effect (ATE) across different configurations.



(a) Loss Curves for Batch Size 16

(b) Predictions vs Ground Truth for Batch Size 32

Figure 1: Loss curves for batch size of 16 and predictions vs ground truth for batch size of 32.

The results indicate that batch size significantly affects learning stability, with optimal configurations leading to improved outcomes. Notably, the training loss for batch size 16 stabilized effectively, while larger batch sizes showed fluctuations, suggesting careful selection of batch size is crucial for performance.

5 CONCLUSION

Our proposed method for causal intervention discovery in personalized diabetes management highlights the importance of tailored strategies that extend beyond traditional approaches. By identifying novel intervention targets and simulating their effects, we aim to provide actionable insights for clinicians. Future work will focus on refining these methodologies and assessing their generalizability across diverse populations.

REFERENCES

SUPPLEMENTARY MATERIAL

Additional details, including hyperparameters such as learning rates and configurations used during training, will be provided in the supplementary material. We will also include figures demonstrating loss curves with various configurations.