Thank you for giving us valuable comments. GluConv is the model of time series forecasting designed for glucose monitoring. It is an honor to submit our work to ICASSP 2026. Our implementation is available at GitHub and hope it can be treated well.

For comments from two reviewers, we respond to them respectively. Restricted by the count limitation, we herein provide a detailed reply letter.

For Reviewer **57FF:**

Thank the reviewer 57FF for the comments helping improve the quality of our work.

Comment 1.1: Why GluConv performs much worse when applied on the Dubosson dataset than on others?

Response: We suspect that the performance is attributed to data distribution of Dubosson. Dubosson has the smallest time steps of 8056 among the five datasets as shown in **Table R1**. In statistical analysis, an insufficient sample size is more prone to deviations from the behavior predicted by the Law of Large Numbers and the Central Limit Theorem. Accordingly, we hypothesize that the Dubosson distribution does not strictly follow a right-skewed pattern, which in turn contributes to its suboptimal performance. The glucose level distributions of the selected datasets are illustrated in **Fig. R1**. However, in our work, we take the median as the mean due to that the other four datasets display right skewness.

Due to the page limitation and as we have done some work in our current work, we decide to not include this explanation in the re-submission version but will keep the explanation on the GitHub/README.md. Please focus on our future work on certain journal.

Datasets	CGM Device	Variates	Timesteps	Diabetes	Subjects	Age	Sex (M/F)	Lower BG	Upper BG
Broll [30]	Dexcom G4	3	13,866	Type-II	5	NA	NA	20mg/dL	400mg/dL
Colas [31]	MiniMed iPro	10	114,253	Mixed	201	59	100/100	20mg/dL	400mg/dL
Dubosson [32]	MiniMed iPro2	14	8,056	Type-I	7	NA	NA	20mg/dL	400mg/dL
Hall [33]	Dexcom G4	51	105,426	Mixed	56	48	NA	20mg/dL	400mg/dL
Weinstock [34]	Dexcom G4	31	647,859	Type-I	192	NA	101/91	20mg/dL	400mg/dL

Table R1. The heterogeneous nature of the processed datasets

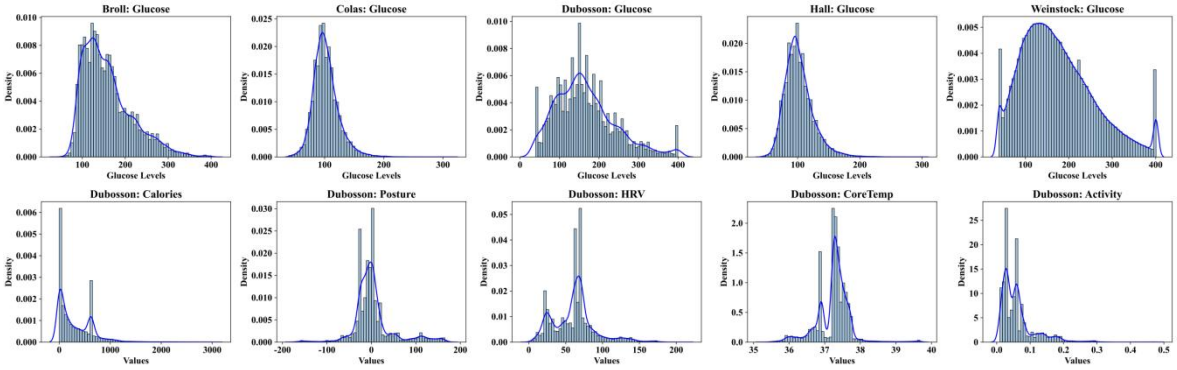

Fig R1. The glucose level distributions for the 5 datasets, along with the distributions of the remaining 5 features in the Dubosson. The feature distributions of Dubosson exhibit clear multi-modality and heavy tails.

Comment 1.2: Why the training time of XGBoost on the Weinstock dataset appears much larger than any other case?

Response: We are sorry that we mistakenly transformed the unit of the **Training Time Per Epoch of XGBoost** in **Fig. 2**. We re-launch the experiment of XGBoost on the Weinstock and record the training time. The average training time is about 3500 ms. The log of experiment can be found on GitHub/outlier_xgboost_weinstock.txt. By searching "Average Training Time" in this file, it is confirmed that the training time per epoch of XGBoost is around 3.45s rather than 3500s reported in **Fig.2**. We mistook ***ms*** as ***s*** in XGBoost and we have corrected **Fig.2** in GluConv_Resubmission.pdf.

Comment 1.3: Some of the acronyms are used without claiming, e.g., CNN/RNN/UNet, etc.

Response: Thank you for pointing this out. We revise the manuscript to define all acronyms at their first occurrence, including CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), and U-Net.

For Reviewer **24D2**, thanks for your comments but we have sufficient evidence to doubt the comments are *unfair***:**

Comment 2.1: Scope relevance is marginal

Response: As introduced at the beginning, GluConv belongs to the field of signal processing and time series forecasting, which is fully aligned with the scope of ICASSP.

Comment 2.2: Minor writing issues such as a comma

Response: We note a potential inconsistency between the comment and the rating for Q8. The reviewer indicated *minor writing issues*, while Q8 represents *serious structural and language issues*. We think Q8 is unreasonable and wonder why there is a paradox.

Regarding the writing quality, we have carefully revised the comma issue and conducted thorough proofreading of the entire paper to further improve readability.

Comment 2.3: No link of code can be found

Response: In the first version, we wrote "***our code will be on GitHub***" as we plan to publish all codes when our work is accepted. Now, Our code is released on GitHub.

Comment 2.4: The model architecture is overly simple and lacks novelty

Response: GluConv integrates U-Net with the convolutional module, which is designed under the consideration of the characteristics of the glucose datasets. The motivation for adopting the convolutional module lies in mitigating the high memory consumption of U-Net and obtain sufficient receptive fields. As a result, the architecture represents a trade-off between complexity and efficiency. Besides, we take two branches in GluConv, because there are two kinds of diabetes: Type-I and Type-II and the five datasets we adopt have both types. Every module is designed under a careful thinking. In the end, we want to argue that the whole structure of GluConv as shown in **Fig. R2** is not simple. Even if someone considers it overly simple, it is effective and holds the beauty of simplicity and effectiveness. Therefore, we can take that the reviewer marks a low score due to this ridiculous reason.

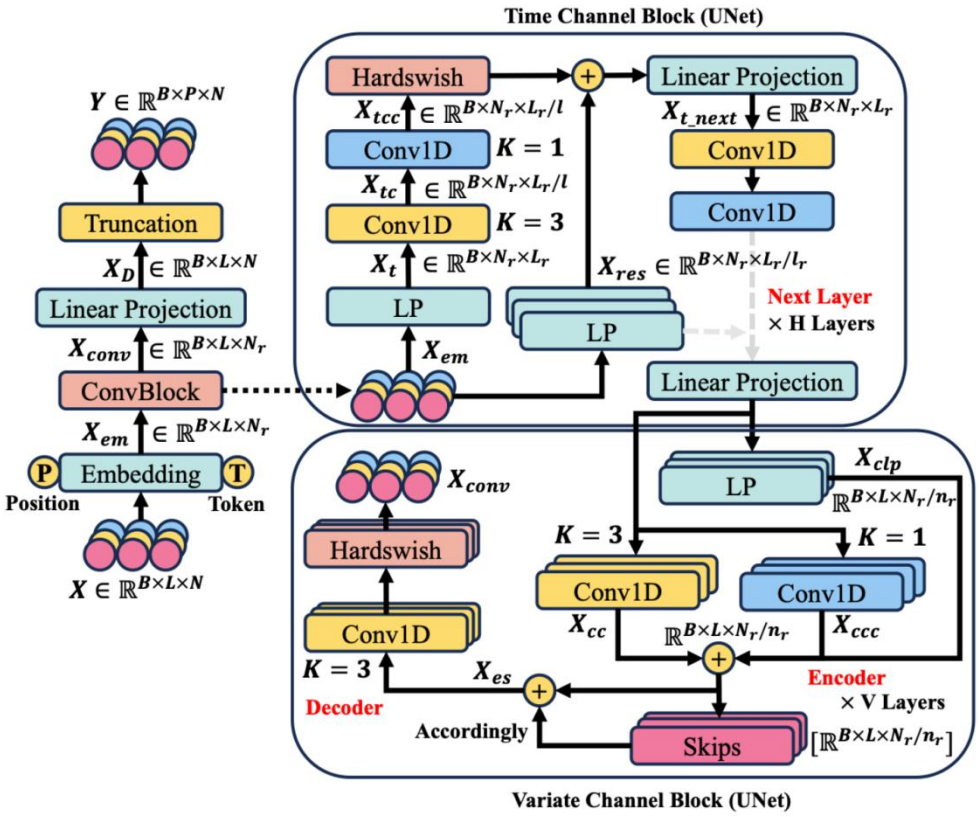

Fig R2. The architecture of GluConv which contains U-Net and Convolutional modules. GluConv is not overly simple.

Comment 2.5: The experimental validation lacks in some respect; The technical contribution is insufficient

Response: We disagree with this comment. Given the 5-page limit for the main paper, we still tried providing a comprehensive yet concise experimental evaluation. The accuracy (MSE, MAE), likelihood and calibration are measured in our main experiments.In addition, We also measure **training time** and **memory** cost in **Fig. 2.**

The MSE and MAE measure the accuracy. The likelihood and calibration verify the trustworthiness. The training time and memory measurements confirm the responsiveness. The introduction of noise in training but GluConv still beats other benchmarks, as well as the publication of our code, confirm the robustness.

All these experiments are adhere to our core statement that GluConv is a **Conv**cing (accurate and trustworthy), **Conv**olutional (responsiveness), **Conv**enient (Robustness) in our Abstract.

Comment 2.6: Some of the references are of limited relevance

Response: We disagree with this comment. We cite a total of 20+ references, all of which are carefully selected to ensure their relevance to the scope of this study. A full page of references cannot treat the reviewer, we wonder how many references are required?

Comment 2.7: The connection between the method and the experiments is unclear, and the writing is disorganized. For example, why is the uncertainty for your proposed method shown as "–" in Table 1?

Response: We have already clarified "–" in the caption of **Table 1** that "–" represents there is no such measurement on models. Uncertainty measurements cannot be applied in some machine learning-based methods in this study. Besides, the connection between the proposed method and the experimental evaluation is explicitly described in the methodology and experimental sections. In addition, at least we deliberately explain the Conv of GluConv as **Conv**cing, **Conv**olutional, **Conv**enient, which shows we write our work with great heart.

We beg AC to have a look at our work and determine whether it is disorganized.

In conclusion, we sincerely thank Reviewer **57FF** for the constructive comments, which have helped us improve the clarity and quality of the manuscript.

Regarding the concerns raised by Reviewer **24D2**, we still have carefully addressed each point and provided detailed clarifications and supporting evidence to explain why we believe these concerns are based on misunderstandings. We hope that our responses adequately clarify these issues and demonstrate the validity of our work.