Adapting TimelyGPT Model for Patient Laboratory Test Value Forecasting

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Jiacheng Zhou

Jiacheng (Joyce) Zhou is a master’s student in Biomedical Engineering at Columbia University. Her research focuses on predictive modeling of patient trajectories using electronic health records and medical imaging data. She is particularly interested in developing deep learning frameworks for modeling irregular and longitudinal clinical data.

Background

- Patient Electronic Health Records (EHRs) provide rich information for predictive modeling.
- Timely Generative Pre-trained Transformer (TimelyGPT) (Song et al., 2025)
  - Trained on two large-scale patient EHR datasets
  - Capable of:
    - Predicting continuous biological signals over a short time period
    - Forecasting diagnoses for patients based on irregularly sampled medical records.
  - Limitation: no evaluation on the model's ability to predict the exact values of irregularly scheduled laboratory tests.

We extend the current TimelyGPT framework for predicting **common and sparse irregularly sampled** patient laboratory values, using White Blood Cell (WBC) count and N-Terminus pro-Brain Natriuretic Peptide (NT-proBNP) as proof-of-principle parameters.

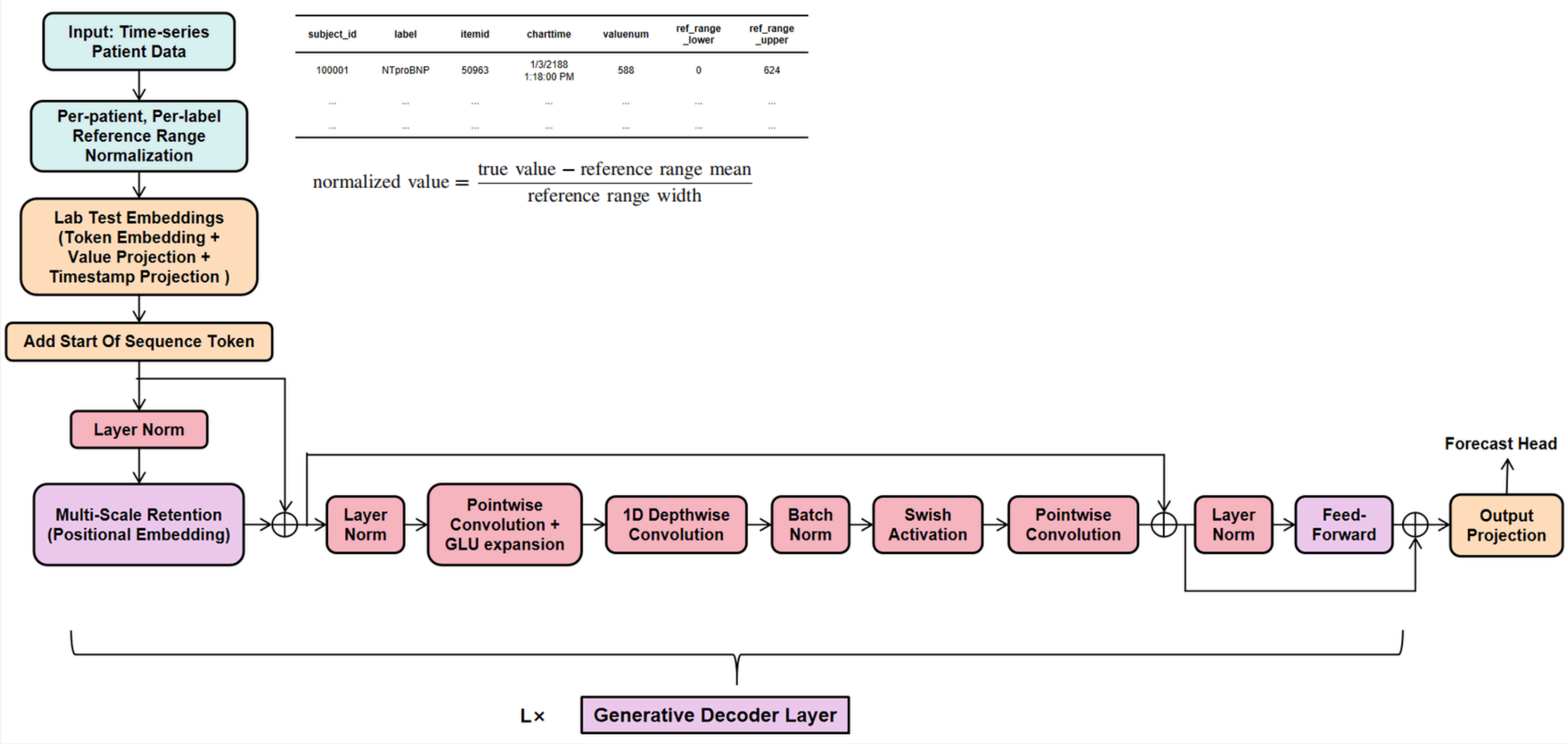
Methods

Dataset and Preprocessing:

- Hospital data from the deidentified MIMIC-IV v3.1 dataset
- Patient filtering:
  - For NT-proBNP:
    - ≥ 6 timestamps
    - ≥ 4 NT-proBNP measurements
  - For WBC count:
    - ≥ 6 relative days
    - ≥ 4 WBC count measurements
- Medication administration records:
  - 98 WBC count-influencing medications were identified
  - Construct daily binary medication indicators
- Train/validation/test splits:
  - Patient-level split (80/10/10)
  - No patient overlap

Methods

Model



subject_id	label	itemid	charttime	valuenum	ref_range_lower	ref_range_upper
100001	NTproBNP	50963	1/3/2188 1:18:00 PM	588	0	624
...	...	...	...	...	...	...
...	...	...	...	...	...	...

$$\text{normalized value} = \frac{\text{true value} - \text{reference range mean}}{\text{reference range width}}$$

Results

- Forecasting WBC counts: predict the next 3 days using the past 3 days
- Normalized prediction errors: clustered around 0, with a mean of 0.62 and a standard deviation of 0.97
- Incorporating medications: mean error reduced to 0.23 with a more compact distribution

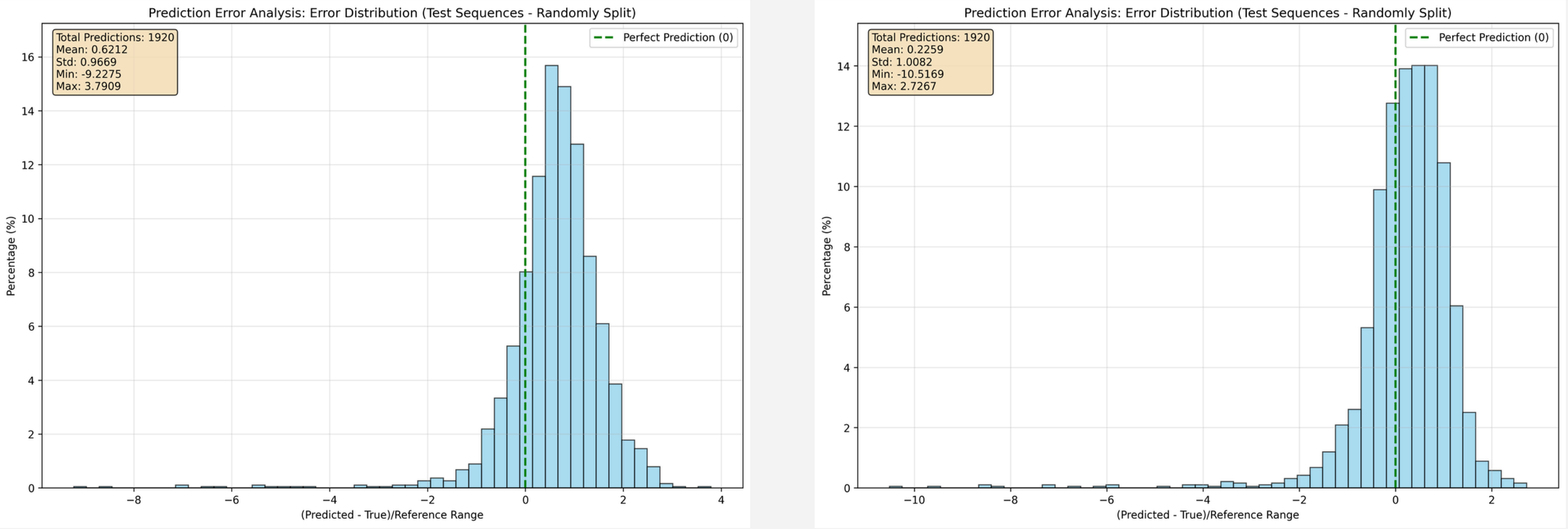


Figure 1. Error distribution of all test sequences for WBC with (right) and without (left) medication input

Results

- Forecasting NT-proBNP: predict the next 3 timestamps from the previous 3
- Normalized prediction errors: centered around 0 (low bias)

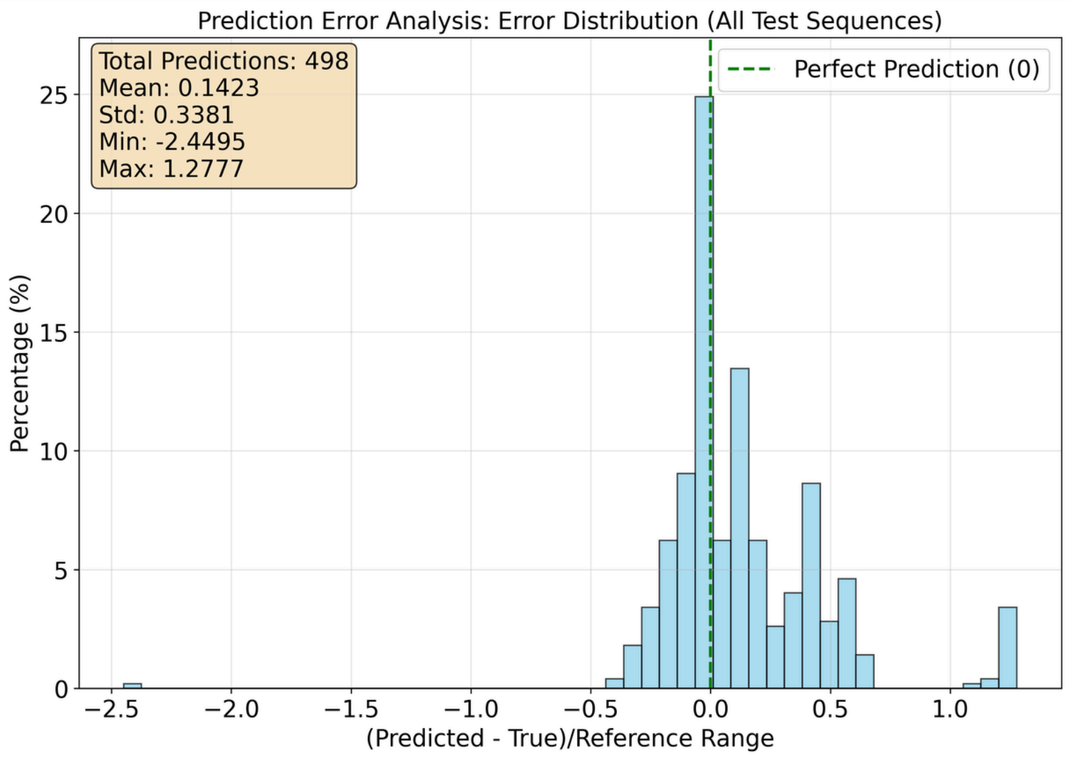
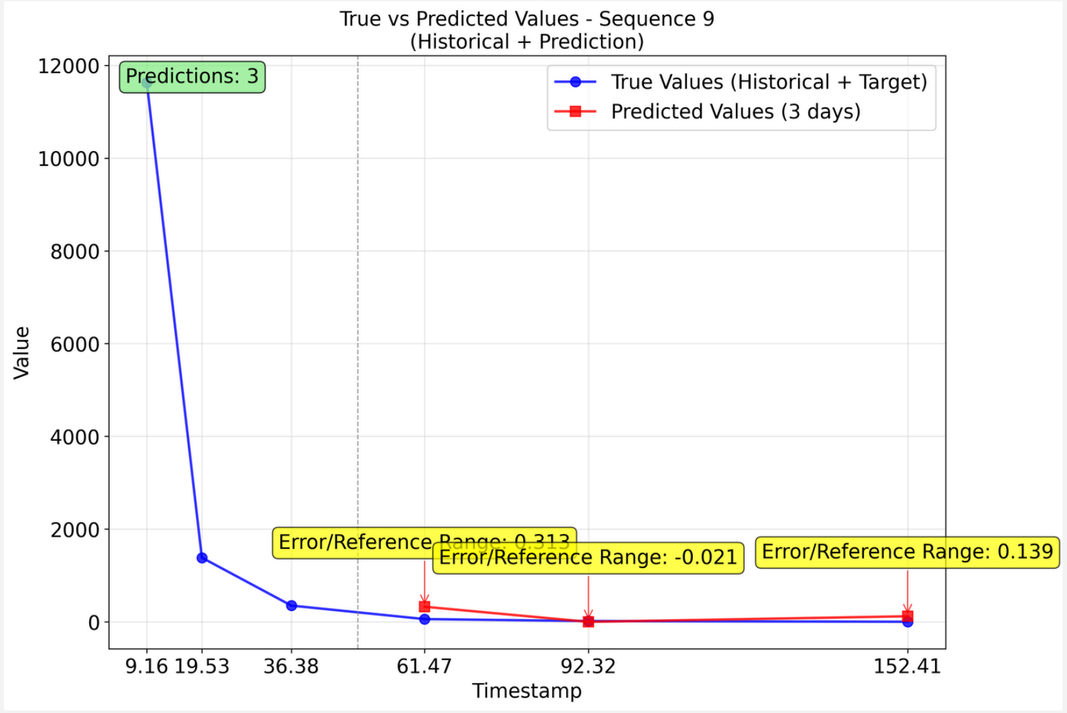


Figure 2. Error distribution of all test sequences for NT-proBNP.

Results



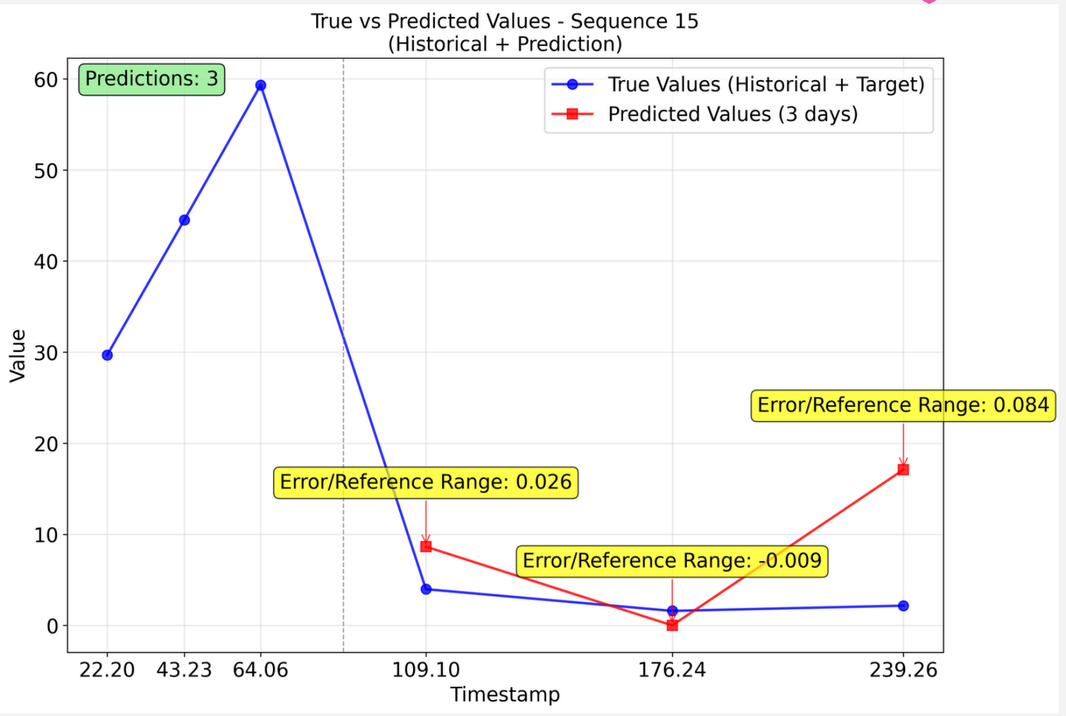


Figure 3. Plots of forecast values versus true values of NT-proBNP.

Conclusions

1. Adapting the TimelyGPT model for **single-label** and **irregularly sampled** healthcare parameter forecasting is feasible.
2. Incorporating **medication administrations** might further enhance the model's ability to capture laboratory trajectories.

Limitations & Future Work

Limitations:

1. Evaluation of WBC count prediction limited to patients' first six days.
2. NT-proBNP value predictions are generated at discrete timestamps.
3. Error margins are not yet sufficient for direct clinical deployment.
4. Results represent proof-of-concept for predicting irregularly sampled laboratory values.

Future directions:

1. Extend model training to outpatient data from the Integrating Numerous Sources for Prognostic Evaluation of Clinical Timelines (INSPECT) database.
2. Evaluate outpatient versus inpatient prediction.
3. Explore novel data augmentation methods.
4. Integrate the administration of medications affecting NT-proBNP value as an additional input.

References

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