Resolution-Dependent Analysis of Time Series Forecasting Performance: A Comparative Study Using Correlative Multi-Datasets

TaeGyu Yang[1] and Kyung-Ah Sohn[1,2]

[1] Department of Software and Computer Engineering, Ajou University, Suwon 16499, Republic of Korea
[2] Department of Artificial Intelligence, Ajou University, Suwon 16499, Republic of Korea

Corresponding author: Kyung-Ah Sohn

Abstract

Data is continuously generated across various domains, and time series data, recorded in chronological order, plays a crucial role in forecasting. Effectively utilizing such time series data can significantly aid in risk management and decision-making across diverse fields, including healthcare, finance, and industrial operations. This study focuses on predicting healthcare time series data. Unlike other signal data, healthcare time series data is characterized by long sequences of data for multiple patients. This study aims to effectively capture and learn the unique features of healthcare time series data.

Keywords*— *Deep Learning, Machine Learning, Time Series Forecasting

I. Introduction

Time series data forecasting traditionally relies on a single long sensor data stream, such as the ETT[4] dataset. However, healthcare data incorporates multiple patient time series that exhibit similar patterns but vary in signal form. Unlike typical datasets, healthcare time series data is infrequently used as a baseline dataset for time series forecasting. Although there have been studies on healthcare time series data for classification and anomaly detection, its application in forecasting has not been fully explored. This study investigates whether models effective in other domains can achieve high performance with healthcare data. We specifically focus on refining resolution guidance to improve prediction accuracy. Predicting future events based on long-term healthcare data can significantly aid risk management across various applications.

Currently, research on time series data involves models ranging from Multi-layer perceptron (MLP) and Transformers [2] to recent generative models like Diffusion. We specifically focus on utilizing Transformer models. Healthcare data often has resolutions in seconds rather than minutes or hours, frequently resulting in long-term sequences with time steps (window size) exceeding 48. Leveraging the Transformer's strength in handling long sequences, we predict that training on healthcare data will yield promising results.

II. Methods

A. Problem Definition

The objective is to predict the subsequent 24 time steps of data using a time series sequence of the preceding 96 steps. This task falls under the category of long-term sequence prediction, as the combined length of the input sequence and the predicted sequence exceeds 48 time steps [4].

B. Dataset

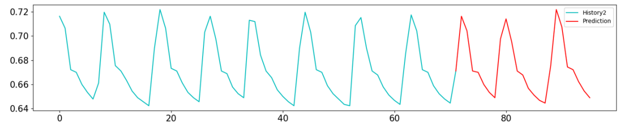

Fig. 1. Arterial Blood Pressure (ABP) of VitalDB[1] dataset

The dataset used in this study consists of time series sensor data from VitalDB [1], focusing on blood pressure measurements, which exhibit periodic patterns, as illustrated in Fig. 1. Segments of the data where blood pressure values are excessively low or high were excluded as outliers to prevent adverse effects on the training process. The dataset includes data from a total of 3301 patients. The original data, recorded at 100 frames per second, was downsampled to 5 and 10 frames per second for comparative experiments focused on varying input resolutions. After downsampling, the data underwent standardization. The data was then split into training, validation, and test sets in an 8:1:1 ratio.

C. Models

Time series data analysis models typically focus on two key characteristics: trend, which indicates whether the model is monotonically increasing or decreasing, and periodicity, which indicates whether the data repeats based on a specific period. Optimizing input size can enhance these characteristics for use in training. This study conducts a comparative analysis of model performance by varying input resolutions. We specifically explore the capabilities of recently proposed models such as Informer[4], FEDformer [5], and Diffusion-TS [3].

Compared to the vanilla Transformer [2], Informer [4] employs ProbSparse identifies and utilizes the dominant query-key pairs that significantly impact learning during attention computation. By using the top-u queries in a sparse matrix, the computational complexity of attention is reduced.

FEDformer [5] integrates the Fourier transform to capture periodic patterns in time series data, transforming it into the frequency domain to better utilize periodic components for forecasting. The model decomposes time series data into periodic and trend components by passing raw data through multiple kernels of different sizes. The values from these kernels are weighted via a softmax function to extract the trend component, and the periodic data is obtained by subtracting the trend components from the original data.

Diffusion-TS [3] leverages a transformer-based encoder-decoder architecture to capture complex dependencies in time series data by decomposing it into trend, seasonality, and residual components, similar to FEDformer's decomposition into seasonal and trend features. This allows the model to separately handle different aspects of the data for more accurate and interpretable results. By comparing these models, we can understand how applying the same idea using different methods impacts the outcomes.

III. EXPERIMENTS

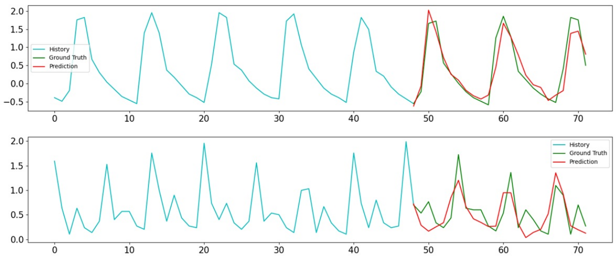

Fig. 2. Forecasted sequence from Informer. Data with distinct periodicity(top) and data with less significant periodicity(bottom).

Fig. 2 illustrates the forecasting results from the Informer model on two example sequences. Although other models also follow the increase and decrease of the sequence to some extent, Informer captures the periodic patterns the best. For sequences with clear periodicity, the ground truth signal (in green) and the prediction(in red) are closely aligned. In cases with irregular patterns, while the accuracy decreases, the model still follows the periodic and trend components to some extent.

Model / MSE	10 Frames	5 Frames
Vanilla Transformer	0.415	0.143
Informer	0.149	0.095
FEDformer	0.183	0.138
Diffusion-TS	0.583	0.352

Table 1. Comparative analysis of model performance for Transformer, Informer, FEDformer, Diffusion-TS based on mean squared error (MSE)

Next, we compare the mean squared error (MSE) of each model under two resolution settings. The results are summarized in Table 1. Generally, reducing the frames per second improves performance. When the resolution is high and a single sequence contains abundant information, the periodicity and trends over time can be lost during processing. Additionally, the training performance varies depending on the input resolution used for learning the same data.

Overall, the transformer-based models outperformed the diffusion-based model, showing better performance at lower resolutions. Among them, Informer demonstrated the best performance at both resolutions. This suggests that utilizing a few dominant keys and queries for prediction leads to better performance, similar to how signal processing filters remove noise by focusing on dominant values. While FEDformer performs better than the vanilla Transformer, it does not outperform Informer. This could be because blood pressure data does not exhibit significant trends within a certain range, thereby diminishing FEDformer's advantages. On the other hand, Diffusion models perform worse than transformer-based models because they are more suited for short-term forecasting. Adjusting hyperparameters like the number of sampling steps or the noise intensity does not result in accurate predictions for short-term scenarios.

IV. CONCLUSION

In this study, we investigated the performance of recent Transformer-based models for time-series forecasting by applying them to multi-sample healthcare data. In the context of medical data, it is crucial to apply appropriate filters and preprocessing techniques to each dataset. We found that adjusting the frame rate and resolution leads to better performance than training on raw data. These results suggest that extracting the specific characteristics from each dataset and providing suitable guidance to the model are likely to result in better predictions. In our future work, we plan to broaden the experimental scope to include a broader range of input resolutions and develop precise guidelines for selecting the optimal resolution for biosignal data.

V. ACKNOWLEDGEMENTS

This research was supported by the MSIT(Ministry of Science, ICT), Korea, under the National Program for Excellence in SW(2022-0-01077) supervised by the IITP(Institute of Information communications Technology Planning Evaluation) in 2024

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