Emergency Department Wait Time Prediction based on Cyclical Features by Deep Neural Networks

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Introduction

An effective estimate of patient wait time at emergency departments (ED) significantly improves working efficiency and reduce unnecessary crowding in hospitals globally[1]. Proper forecast models for patient arrival time at ED facilitates both hospital management and waiting patients in early planning and avoids crowding and time wasting. A recent survey compared different machine learning (ML) models to predict wait time in EDs, including regression models, autoregressive integrated moving average (ARIMA) models, artificial neural networks (ANNs). The study concludes that deep neural networks (DNNs) such as long-short term memory (LSTM) networks and convolutional neural networks (CNN) outperform the conventional regression such as linear regression and logistic regression[1]. This conclusion is supported by individual studies where LSTM is used to predict the ED patient wait time in 2-hour interval[2]. In addition, a multicenter study reveals that the ML wait time prediction model can be improved if we can integrate more factors into the prediction model with the time series data. However, the time series data of ED wait time has its unique features. For example, the time intervals are usually uneven because they record the date and time when the patients see the doctors. On the other hand, the ED wait time usually series are stationary without clear seasonality due to the maximum facility accommodation of the hospitals. Therefore, the wait time is affected by multiple factors such as medical resource, human power, etc..

In our study, a dataset which recorded all the patient ED wait time from January 2019 to December 2020 is used for analysis and modeling. (See Figure 1). After detrending, we can observe the ED wait time series are stationary (Dickey-Fuller Test, p=4.9747x10^{-30}). From the autocorrelation graph, we can observe the spikes are in very short lags, reflecting the periodic patterns are likely to repeat in very short time intervals. (See Figure 2)

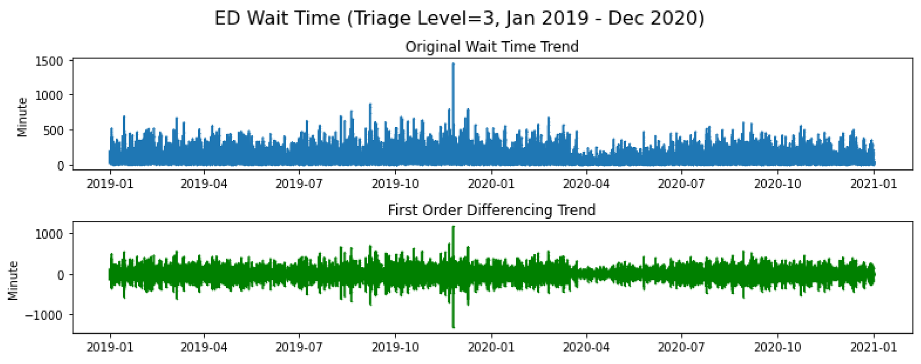

Figure 1 ED Wait Time Series

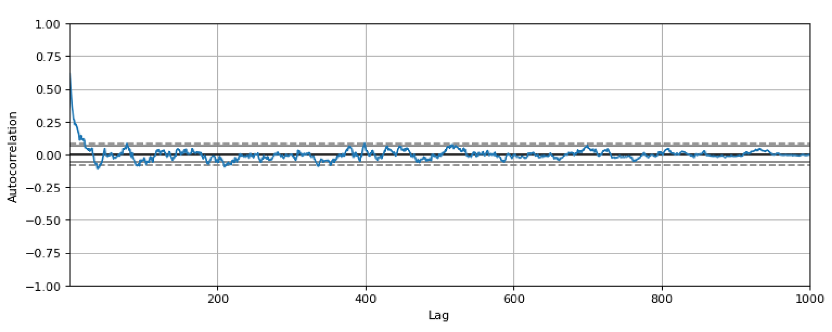

Figure 2 Autocorrelation of the ED Wait Time Series

Our study goal is to examine whether the cyclical features can improve the prediction performance of the DNN based time series models for ED wait time prediction. To extract the time series patterns, we apply the sine and cosine functions to extract the cyclical features from the timestamps of the ED wait time records. By repeatedly computing the cyclical feature based on different time interval units (e.g., from 15 minutes to 1 year), it is hopeful to capture the latent time series pattern from the data. Then we compare the different DNN prediction models with and without the cyclical features to explore whether such features can improve the DNN model performance.

Methods

Unlike other EHR time series data such as ECG (electrocardiography) or body temperature records, the ED wait time data usually does not have an identical time interval. Therefore, to generate time series patterns from these ED records, we extract the cyclical features from the timestamps of the ED visit records by applying the sine and cosine functions. At first, we convert all time stamp information into seconds. Then we generate six pairs of cyclical features given seven time-intervals: 15 minutes, 30 minutes, 1 hour (60 minutes), 1 day, 1 week, 1 month, and 1 year with all quantitative units in second. Then the cyclical patterns are generated based on the following formula:

$$sin(timestamp \times \frac{2 \times \pi}{time\ interval}) \text{ or } cos(timestamp \times \frac{2 \times \pi}{time\ interval})$$

Taking the advantage that the DNN models can model complex functions, we concatenate the 14 generated cyclical features with the original wait time data as the learning patterns for the DNN models. To compare the performance, we also use the original wait time series data only as the input feature to the identical models. Three types of time series models are built for comparison. The single-step with single-output model uses all feature as input to predict the next wait time. The single-step with multiple-outputs models use all features as input to predicts all the features in the next step. The multiple-step models use multiple steps features as input to predict multiple-step-output for the future (i.e., the prediction extends to multiple time points in the future). To build the time series dataset, we arbitrarily set the window size to 30. The architecture of the three time-series dataset is illustrated in Figure 3.

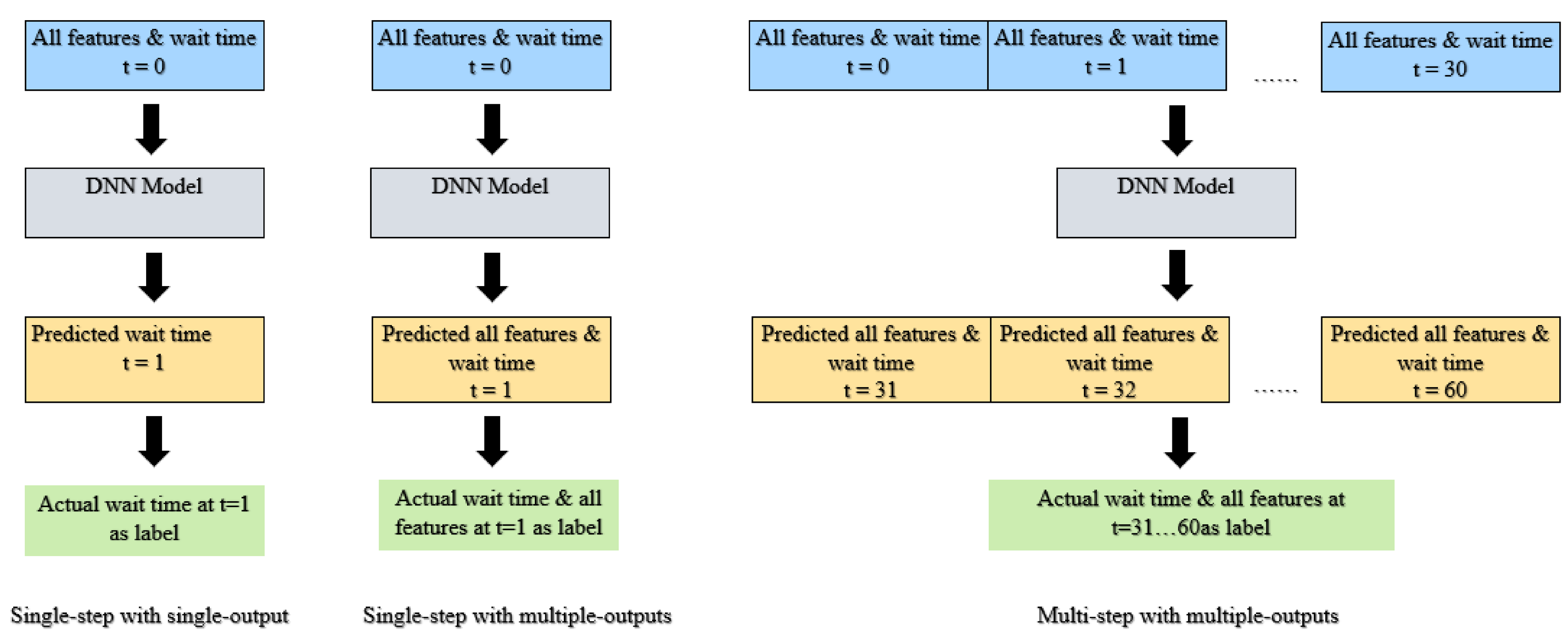

Figure 3 Three type of DNN Time Series Prediction Architecture

In order to find the best DNN architecture, we implemented four types of DNN for the single-step with single-outputs: dense DNN (two dense layers), CNN, LSTM, and LSTM with Autoregressive RNN (AR LSTM). For the single-step with multiple-outputs DNN, we implemented five types: dense DNN, CNN, LSTM, Residual LSTM, and AR LSTM. Finally, we implemented five types of DNN for the multi-step with multiple outputs DNN: multi-linear, dense DNN, CNN, LSTM, and AR LSTM.

The model performance is evaluated by four measures: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE).

All neural network models are implemented in Python with the TensorFlow deep learning package. All the experiments were finished on the Google Colab with Tesla P-100 GPU support.

Results

The models are optimized by 200 epochs in maximum with the Adam optimizer. The initial learning rate is 1x10-4. The original data is sorted and sequentially splitted with 80:10:10, which means 80% of the sequence are used for training, 10% used for validation, and another 10% is used for test. The result is shown on Figure 4.

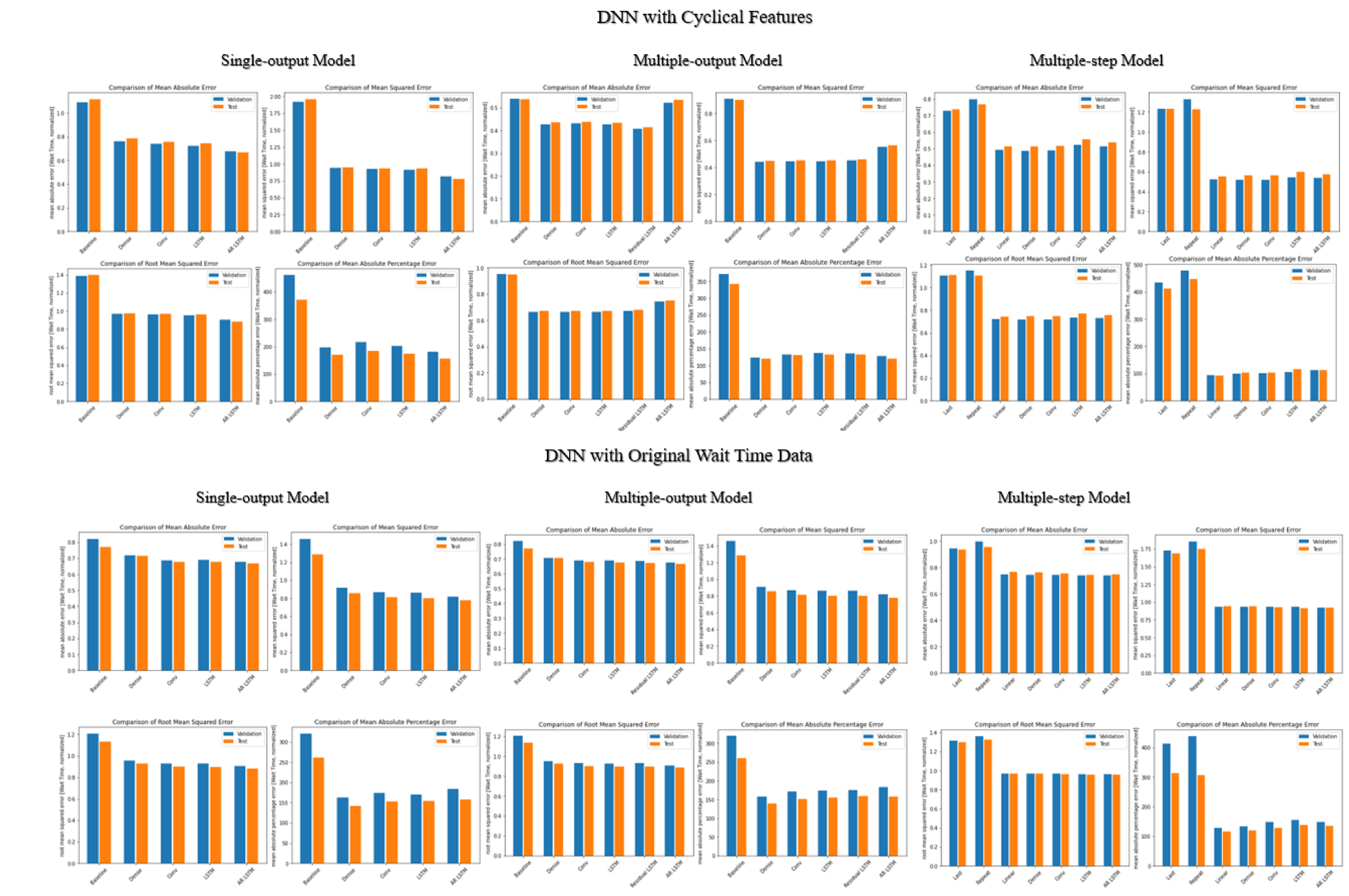

Figure 4 Comparison of Performance

From Figure 4, we can conclude that the cyclical features can mainly improve the performance of the multiple-output DNN models and the multiple-step models. The effect is obvious on the RNN based models such as residual LSTM and the AR LSTM. For example, the MAE of the residual LSTM with multiple-output is 0.4136, compared to MAE=0.6724 by the residual LSTM without the cyclical features. And the MAE of the AR LSTM with multiple-step model is 0.5389, compared to 0.7487 without the cyclical features.

Conclusion

This study is to evaluate if the cyclical features extracted from the timestamp of the ED wait time records can improve the time forecast for patient waiting in the emergency department of hospital. In our experiments, we implement three type of DNN for time series data prediction: single-step with single output, single-step with multiple outputs, and multi-step with multi-output sequence. In addition, we use different neural network architecture such as fully connected network (Dense), convolutional network (CNN) and recurrent neural network (LSTM) to examine which architecture is most suitable for the prediction.

The results implies that the cyclical features can improve the prediction accuracy when the data is fed into a network with multiple outputs. It reflects that the latent time patterns have complex and interactive effect for the prediction. This feature can be shown by the Fast Fourier transfer of all cyclical frequencies. (Figure 5) where it is difficult to find an obvious peak as the main frequency for prediction. If we visualize the optimized weights of the first layer of a train DNN (Dense model), we find that the more weights are allocated to the cyclical feature for the prediction compared to the linear model where the prediction mainly relied on the original wait time.

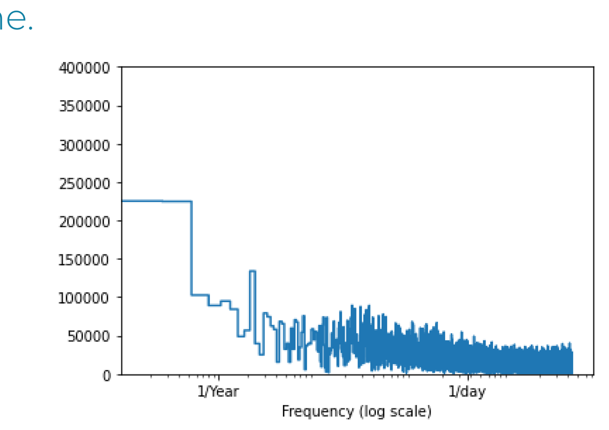

Figure 5 Fast Fourier Transfer of the cyclical time features

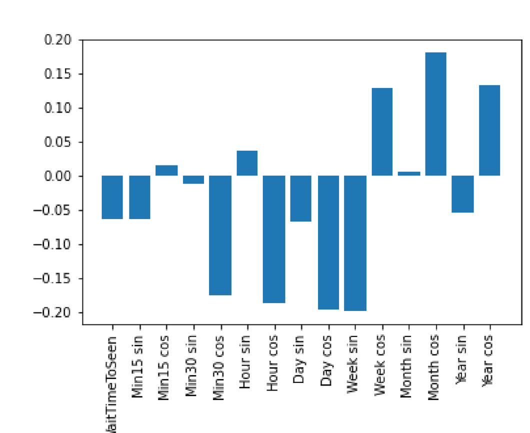

Figure 6 Weights assigned to feature after optimization

In conclusion, using the cyclical features can improve the prediction of ED wait time by DNN. In practice, the feedback from the clinical staff indicates the ensembled models combined with the four best DNN models from the experiment can effectively reduce the estimate error within a 30-minute window, and its performance is superior to the LSTM models only trained by directly retrieved wait time data.

The application of cyclical patterns extracted from EHR time stamps serve as useful features to optimized time series models such as DNNs to successfully predict ED wait time. The errors from uneven time interval can be reduced by transferring the observed features into cyclical feature. We believe this strategy will improve the AI performance in the healthcare systems.

Acknowledgements

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Reference

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