

Analyzing Machine Learning Models that Provide Personalized Heart Rate Forecasting for Elite Cyclists

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Abstract—Performance forecasting in elite cycling is most effective when it is personalized and course-specific to account for the influence of individual and terrain factors. This paper empirically assesses various personalized and course-specific performance forecasting models based on random forest, feed forward neural networks (FFNNs), recurrent neural networks (RNNs), and long short term memory (LSTM). The mean square error (MSE) is selected as the metric for model comparison. The results of our experiments show that the LSTM models have the lowest MSE on both the heart rate forecasting and speed forecasting on our test dataset.

Index Terms—Heart rate forecasting, personalization, cycling course, deep learning

I. INTRODUCTION

A. Background

It is necessary to monitor exercise intensity during elite cycling training. While insufficient exercise may lead to slow improvement in athletes performance, over exertion can result in over-training or even muscle damage. Over-training in cycling can result in a debilitating syndrome that degrades the performance of cyclists for several months and may ultimately result in failure to meet competition goals [1]. Moreover, over-trained athletes—especially those involved in endurance sports like cycling—are susceptible to infections and require significantly longer time for recovery than non-athletes [1], [2].

Several metrics are available to estimate exercise intensity, including heart rate, power output, and $\dot{V}O_{2max}$. According to Jeukendrup et al’s study [3], heart rate is a reliable indicator of exercise intensity in cycling since it is largely independent of a specific course. However, heart rate can be affected by terrain factors, such as grade of the hill, which varies on different riding courses.

Predicting heart rate at different points in time on a cycling course is hard since heart rate is affected by course-specific features, as well as other personalized physiological factors. Research has shown that a cyclist’s heart rate drifts upwards after exercising for 20 to 60 minutes despite unchanged work loads [4], [5], which is a condition called “cardiac drift.”

Cardiac drift is associated with an increase of core body temperature during exercise [6], [7], which may cause athletes

to lower their speed to maintain their heart rate. On the other hand, higher speed can yield a higher heart rate in a given condition [5]. Moreover, heart rate responses vary with a cyclist’s individual factors, such as gender and age [5], as well as their cadence on different parts of a given course.

It is hard to predict heart rate on a specific point in a course at a target speed. Training plans therefore focus on setting target heart rates or power goals (e.g., power applied to the pedals by the rider) and riding as fast as possible without exceeding those targets. Ideally, training plans could be developed where heart rate at a given speed and point in a course is predicted and riders are given a set of target speeds to ride instead. Achieving this ideal, however, requires building heart rate forecasting models that are personalized and course-specific. A personalized performance forecasting model for specific courses is vital for cyclists to establish achievable speed goals at different courses in advance and maximize training effects without over-training.

Another key benefit of personalized course-specific heart rate forecasting is the ability for riders to estimate how much faster they could ride in different sections of the course, yet still remain within heart rate targets. For example, a rider who has only ridden a course at 70-80% of max heart rate could estimate how fast they would ride at a race intensity of up to 90% of max heart rate. This estimate could give them a benchmark of what they could currently achieve without actually riding the course and potentially over-exerting themselves.

For example, a biker may need to climb up on a steep uphill road, which requires significantly slower speeds and greater intensity than a similar climb on smooth ground. Similarly, a high-speed downhill ride on smooth terrain will place less stress on a rider’s core muscle groups compared to the same downhill speed across tree roots. The individual terrain features, turns, gradients, and other aspects of a course significantly impact on a rider’s speed and intensity, but current models are mainly course-independent.

To maximize their efficacy, personalized and course-specific heart rate models should be easily trainable from limited data—ideally a single test ride of a course by an athlete. If an athlete rides a course multiple times at multiple target heart rates, they are unlikely to need a predictive model since they already know the course well. Therefore, new courses (i.e., where the athlete has limited knowledge) are those where personalized and course-specific predictive models are most valuable. Ideal a cyclist should be able to ride a course once and then predict how different target speeds would impact heart rate at different points on the course.

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B. Research Question: Which machine learning approaches perform best for personalized course-specific heart rate prediction from a single ride?

This paper presents our research on comparing personalized multivariate models to forecast the heart rate of a cyclist on a specific course using data from a single ride. These models consider course-specific factors at each part of the course (such as the grade of road and the altitude), as well as current rider details (such as the cadence), and then forecast the heart rate of the athlete based on them. We compare the results of heart rate and speed forecast by the following models from a single ride and report which models perform best:

- The first type of model experimented with is *random forest*, which is a classical machine learning model. Forecasting results show that random forest models have severe overfitting and therefore cannot be utilized in heart rate forecasting from a single ride.
- To mitigate the random forest overfitting problem, we implement *feed forward neural networks* (FFNNs). FFNNs do not exhibit overfitting problems on the dataset, though their forecasting accuracy leaves room for improvement. In particular, FFNNs do not consider historical information when forecasting heart rate.
- To address the limitations with FFNNs, we also implemented two other types of neural networks: *simple recurrent neural networks* (RNNs) and *long short term memory* (LSTM) networks.

We empirically compare all these models via experiments in our testbed. The results of these experiments indicated that the LSTM models have the lowest error among all neural network models and produce predictions that closely match the real-world heart rate sequence.

C. Paper Organization

The remainder of this paper is organized as follows: Section II describes prior work on heart rate forecasting; Section III reviews the data processing methods and all the models applied in this paper, including basic concepts of each model and their pros and cons; Section IV describes how we built Random Forest, feed forward neural network (FFNN), recursive neural network (RNN), and long short term memory (LSTM) models to forecast the heart rate of athletes on a specific route and then compares the best models among these four types with two course-independent models (FitRec [8] and Minmin's LSTM-based model [9]); Section V summarizes the results from our experiments in Section IV; and Section VI presents concluding remarks and outlines future work.

II. RELATED WORK

Researchers have built various models to predict the performance of elite cyclists. Le et al. [5] proposed a mathematical model to evaluate athletes' heart rate response under moderate exercise intensity based on physical and physiological principles. Lucia et al. [10] analyzed the preferred cadence of elite cyclists and found that on flat stages they tend to adopt higher cadences (around 90 rpm) while on mountain

ascents cadences are around 70 rpm. However, their models focus on laboratory conditions. Course-specific factors such as the slope of the road in real courses are unfortunately not taken into consideration which have significant influence on cyclists' heart rate response.

Due to the advent of wearable devices, large amounts of data now can be collected and processed via mobile devices, which offers an opportunity to build personalized performance forecasting models. Mohammadzadeh et al. [11] applied a support vector machine predictor to predict the breathing rate based on the 3-D accelerations, heart rate, body temperature, electrodermal activity, humidity etc. in a controlled lab environment. Ming et al. [12], [13] used a FFNN to investigate the relationship between heart rate and physical activity in daily life with the help of a wearable physical activity recorder which monitors the 3-D accelerations of the body.

RNNs exhibit sequential correlation and can seamlessly model problems with multiple inputs. These models are therefore widely used in natural language processing and time series prediction [14]. In athletic performance forecasting, RNN based models can take personalized factors (such as blood pressure and running speed during exercise) to make a heart rate predictions. Ni et al. [8] proposed an LSTM-based model to learn a user's heart rate profile during exercise and offer workout route recommendation and short term heart rate prediction. Luo et al. [9] also proposed an LSTM-based model to predict heart rate based on heart rate signal, gender, age, accelerations and mental state. Bian et al. [4] tracked facial key points from each frame of facial videos to estimate heart rate.

In summary, although there are other performance forecasting models, most studies focus on the heart rate profile collected either during daily activities or under laboratory conditions. There are few models that are course-specific and personalized to forecast a cyclist's heart rate and speed. However, such a model can be beneficial to both cyclists and coaches.

For example, a cyclist needs a model to set up various speed goals at different parts of a course before a competition or predict their heart rate based on given speed goals. A coach can use such a model to evaluate the heart rate of a given athlete on a given course at a given speed to ensure the exercise intensity and avoid over-training. Likewise, when given specific heart rate goals, these models can be used to predict how fast a cyclist can/should ride at different parts of a course.

III. METHODOLOGY

To address the limited understanding of personalized and course-specific heart rate forecasting from a single ride, we evaluated the performance of prior course/cyclist-independent models, course/cyclist-specific traditional machine learning models, and course/cyclist-specific deep learning models on forecasting rider heart rate on a single ride of a course. These comparisons allowed us to investigate a number of important research questions and collect important lessons learned to guide future research, as discussed in this section.

A. Key Research Questions

The key research questions we investigated in our study include the following:

- Are current models that do not consider course-specific features as good as models that consider specific features, such as location?
- Do traditional machine learning or deep learning techniques perform better on course-specific heart rate forecasting?
- For traditional machine learning models, which features are most salient for learning?

B. Experimentation Approach

We first surveyed prior work on heart rate forecasting and then selected and applied both traditional and deep learning models to a cycling dataset that we collected. Important cyclist and course-specific factors must be considered for cycling performance forecasting. It is natural to consider multivariate models for performance forecasting, e.g., random forest and neural networks are popular machine learning algorithms because they can be utilized both for regression and classification and can handle multiple inputs. The flow chart in Figure 1 outlines key procedures associated with heart rate forecasting.

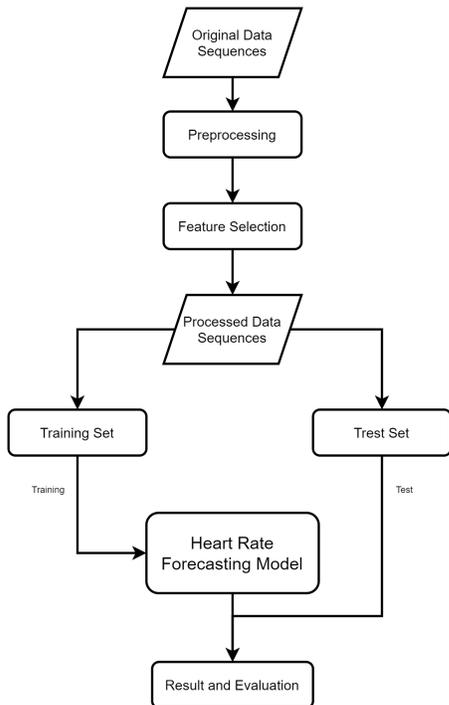


Fig. 1: Heart Rate Forecasting Procedures

According to Leijnen et al. [15], there are 13 major neural network architectures used by researchers in performance forecasting, including feed forward neural networks (FFNN) [12], [13], basic recurrent neural networks (RNN) [16], and long short term memory (LSTM) [4], [8] models. We therefore selected these three neural networks and random forest and built a personalized model to predict the performance of a cyclist on a specific routes. LSTM is a special type of RNN,

so to distinguish these two models we call basic RNN models “simple RNN” models in this paper.

In the performance forecasting problem, an athlete’s performance is affected by numerous features, such as temperature and the grade of course. Not all these factors, however, should be provided as input to a traditional machine learning model. For example, random forest models are sensitive to data variation, so tiny differences in the dataset can cause a large variance in the prediction.

Pruning irrelevant features to an athlete’s performance can reduce model overfitting and improve forecasting accuracy. Neural networks have built-in mechanisms to mitigate overfitting and perform feature selection by assigning significant features larger weights. This process, however, consumes a large amount of time and requires a large amount of data. Removing less important factors can accelerate the training process of neural networks and reduce the amount of data needed. This paper therefore uses feature selection for both random forest and neural networks.

In statistics, a correlation coefficient is used to characterize how strong a relationship is between two variables. This coefficient is a real number between -1 and $+1$. The absolute value of correlation coefficient shows the strength of a relationship.

For example, assume there is a cyclist riding on a plane with constant velocity and direction. Assume there are two factors, one is the velocity of the cyclist, denoted as v , and the other is the color of the bike, denoted as c . Based on the property of uniform linear motion, the distance d can be described as the product of cyclist velocity v and time t .

To build a distance forecasting model, v rather than c should be taken into consideration. The correlation coefficient between v and d is $\rho_{v,d} = 1$ while that between c and d is $\rho_{c,d} = 0$, which shows that there is a linear relationship between v and d while c and d are uncorrelated. By calculating and comparing correlation coefficients between features and the target value, significant features can thus be extracted and irrelevant features can be filtered.

Two common correlation coefficients are widely used: the Pearson correlation coefficient and the Spearman’s rank correlation coefficient. Pearson’s correlation coefficient assesses linear correlation [17]. In contrast, Spearman’s rank correlation coefficient focuses on the monotonic relationship between two random variables [18].

According to Bishara et al. [19], calculating Spearman’s correlation coefficient for non-normal data may be an optimal strategy when the data size is larger than 20. For performance forecasting, the heart rate and velocity of a cyclist shows complex non-linear relationships with factors like cadence and the grade of the road when the total number of data items is far more than 20. Spearman’s rank correlation coefficient is more suitable for calculating the correlation coefficient, so we therefore select this approach to filter the personalized and terrain factors compared with Pearson’s correlation coefficient.

For Spearman’s rank correlation coefficient, raw data (such as heart rate, speed, and the grade of course) should be converted to rank variables. Given a heart rate sequence HR , where hr is a heart rate in this sequence, the rank variable r_{hr} of hr is obtained as follows [20]:

- Sort HR in ascending order and denote the sorted heart rate sequence as HR_s
- The position where hr is in HR_s is the rank variable r_{hr} of hr

For example, given a heart rate sequence over 4 seconds are $\{100, 102, 95, 86\}$, the corresponding rank value for this heart rate sequence is $\{3, 4, 2, 1\}$.

Assume there are two data sequences (e.g., X and Y) each of which has n examples. Based on the method described above, two ranked sequences rg_X and rg_Y can be obtained. The formula for Spearman's correlation coefficient [20] is expressed in Formula 1,

$$\rho_{rg_X, rg_Y} = \frac{cov(rg_X, rg_Y)}{\sigma_{rg_X} \sigma_{rg_Y}} \quad (1)$$

where $cov(rg_X, rg_Y)$ is the covariance of ranked sequences rg_X and rg_Y , while σ_{rg_X} and σ_{rg_Y} are the standard deviations of the ranked sequences.

C. Overview of Our Dataset

For heart rate forecasting, the dataset used in this paper contains the grade of course, speed, heart rate, altitude, cadence, and distance at each second. We are interested in understanding how course-specific features impacted forecasting performance. We therefore use mountain biking data from trails in the Nashville, Tennessee, USA region.

Mountain biking courses have significant terrain-based variation, ranging from rocks and roots to very steep up-hill sections, to mud. These variations in terrain lead to large variation in the physiological demands on the rider. These variations affect the muscles used, such as core and shoulder muscle engagement when riding over rocky terrain.

Our dataset was collected on a Ripmo AF mountain bike instrumented with a Garmin 830 biking computer connected to a accelerometer-based speed sensor mounted to the front hub of the bike. The bike's crank arms included a Quarq Sram XX1 Eagle Dub power meter that used embedded strain gauges to measure the power applied to the pedals within +/- 2%. The Quarq power meter directly measured the rider's pedaling cadence from accelerometers embedded in the crank arms. The Garmin 830 included GPS positioning and improved location tracking using a fusion of wheel rotation, speed, and GPS fix data. Finally, a Wahoo Tickr electrode-based chest strap was used to measure heart rate and communicate the data to the Garmin 830.

For our study, we selected 8.71 miles of riding on a 10-mile courses in the Nashville area. The rider was a 40-year old male weighing approximately 210 pounds.¹ In cycling, functional threshold power (FTP) is commonly used to measure cyclist fitness. FTP estimates the maximum power that can be sustained by a cyclist for one hour. The FTP for the data collection cyclist was 240 measured using an indoor cycling trainer with a ramp testing protocol.

¹A weakness of the current work is our focus on a single rider, but we chose to focus on one rider to maximize understanding of how course-specific features could be learned since individual riders have been more thoroughly studied in prior work.

Our dataset and the source code that we used to evaluate all the models discussed in this paper is available from github.com/EricXQiu/SportDataProcessing.

D. Feature Selection

The first step in our dataset processing involved selecting features for model training. Before selecting features, the significance of these sequences must be determined. Spearman's correlation coefficients (ρ) for each of these sequences are listed in Table I. This table shows that the grade of course,

Features	Spearman correlation coefficient
speed	0.1826
grade of course	0.2524
cadence	0.2389
distance	0.0466
altitude	0.2586

TABLE I: Spearman Correlation Coefficient Between Factors and Heart Rate

cadence, speed, and altitude significantly influence heart rate more than the other factors. We therefore selected these four factors as the features for our heart rate forecasting model.

We measured heart rate data with an electrode sensor on a chest strap. During cycling, the sensor might situate far apart from the skin due to motion, which can cause error on heart rate data. To reduce the error and smooth the heart rate, the heart rate sequence was therefore processed with a window average of 60 seconds. The grade of course, cadence, speed, and altitude features are also processed with the same window average process to ensure consistency with the heart rate data.

We split the dataset between a training set and test set. By convention, we used an 80% vs 20% train-test split ratio to split data into the training set and test set. For the LSTM-based model, the training set was the first 80% of the data and the test set was the remaining 20% rather than a random selection to account for the order dependence in heart rate data. To compare the results with LSTM-based models, the same train-test split process was also performed for the random forest model.

IV. HEART RATE FORECASTING MODEL COMPARISON

This section describes how we applied four learning algorithms (random forest, feed forward neural networks, simple recurrent neural networks, and long short term memory) to build heart rate forecasting models that predict an cyclist's heart rate on a given course. The results of applying these heart rate forecasting models are then analyzed. We also compare the mean squared error (MSE) of all four models to glean insights into which models perform best and whether they have severe overfitting. Finally, we compare our models with other models (Ni's model [8] and Luo's model [9]) that are *not* course-specific, but which we trained on our dataset described in Section III-C.

A. Random Forest Heart Rate Models

We used the scikit-learn library [21] to construct the heart rate forecasting models based on random forest. The criterion

is MSE and the number of decision tree regressors can be modified. Table II shows four random forest models with different numbers of decision trees regressors.

Model Number	#Decision Tree Regressors
1	5
2	10
3	15
4	20

TABLE II: Number of Decision Tree Regressors in RF model

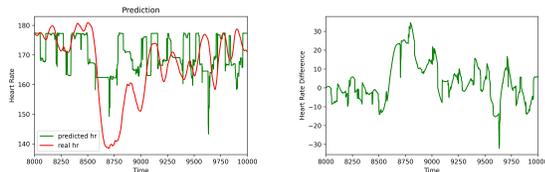
Each decision tree regressor uses all factors in regression. Their MSE on the training set and test set, as well as the maximum depth of decision tree regressor, are shown in Table III. For all four models, the MSE on the test set are hundreds

RF Model	MSE on Training Set	MSE on Test Set	Max Depth
Model 1	0.455	125.15	31
Model 2	0.245	120.39	30
Model 3	0.157	130.40	34
Model 4	0.289	128.92	34

TABLE III: MSE and MaxDepth of RF Models on Data Set

of times larger than on the training set, which shows that these random forest models have severe overfitting. Table III shows the depth of decision tree regressors are approximately six times larger than the number of factors. This result indicates some factors are split multiple times, which increases the complexity of the decision tree, thereby yielding severe overfitting of the random forest model.

The heart rate forecasting result of model 1 is chosen and shown in Figure 2a. The predicted value follows the trend of



(a) Forecasting Result (b) Prediction Error

Fig. 2: Heart Rate Forecasting of Random Forest Model 1

the heart rate and shows the model learned some patterns in the heart rate sequence due to the course. However, the predicted heart rate shows a large error around time 8,900s. Moreover, the predicted heart rate remains stable for the time range from 8,600s to 8,700s, whereas the real heart rate shows a sharp decreasing trend. The error in percentage between predicted heart rate and real heart rate is shown in Figure 2b, which shows a similar trend as the forecasting result.

To investigate the structure of random forest model, the Gini importance² of each factor is calculated. A factor with large Gini importance means that more nodes are split by this feature in the decision tree and therefore this feature is considered significant.

The average Gini importance of factors in each model is listed in Table IV. This table shows that speed, time, and

²The Gini importance is the average decrease of variance, which indicates the probability of whether there is a split on this feature [22].

RF Model	Gini Importance of Factors (Time, Grade, Speed, Cadence, Altitude)
Model 1	0.294, 0.0376, 0.531, 0.028, 0.108
Model 2	0.280, 0.0344, 0.536, 0.029, 0.120
Model 3	0.281, 0.0342, 0.540, 0.030, 0.113
Model 4	0.285, 0.0349, 0.536, 0.028, 0.115

TABLE IV: Gini Importance of Random Forest Models

altitude are three major factors used to split nodes in the first several layers of decision tree. Likewise, the table also shows the influence of cadence and grade are less important in decision tree construction.

We hypothesize that the source of the error may occur for the following reasons:

- The dataset only indirectly measures course features via speed and position, so it does not effectively learn course-specific influences on heart rate.
- There may be some internal rider conditions, such as the mental activities of the cyclist over time. For example, a cyclist may be anxious due to the difficulty of the terrain, thereby increasing their heart rate. All these features can influence heart rate, though they are hard to measure and express quantitatively.
- The random forest models may overfit on the training set and provide erroneous predictions.

B. The FFNN Heart Rate Model

Due to the overfitting problems of the random forest model, we built feed forward neural network (FFNN) models with different hyper-parameters. The hyper parameters of the FFNN models are listed in Table V.

Model Number	#Layers	#Neurons in Each Layer
1	2	(5, 1)
2	2	(10, 1)
3	3	(5, 5, 1)
4	3	(10, 5, 1)

TABLE V: Hyper-Parameters of FFNN Models

An important phase of training a neural network involves finding a proper learning rate. To search the learning rate systematically, we employed Smith's method [23]. By running at each learning rate for 10 epochs, the loss vs learning rate curves are plotted, as shown in Figure 3. According to the curves, the optimal start learning rate for these four FFNN models are 3×10^{-2} .

Figure 4 shows the predicted heart rate and the real heart rate of these four FFNN models applied to the same sample as the random forest. The sample shows that FFNN models can follow the trend of the cyclist's heart rate on the specific course. The error and error percentage are plotted in Figure 5 and Figure 6, respectively.

Models 3 and 4 show large errors from 8,500s to 9,000s. To investigate the error source, MSEs of the training set and test set are calculated for these four models, as shown in Table VI. Model 3 shows an obvious overfitting on the training set, while Models 1 and 2 show large bias on the training set. Among these four models, Model 4 shows relatively low bias and variance.

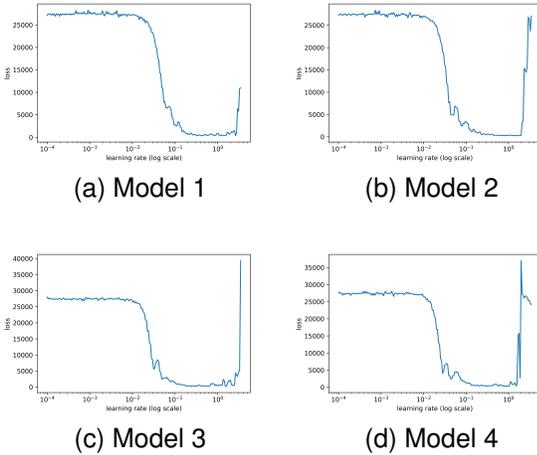


Fig. 3: Learning Rate Search for FFNN Heart Rate Models

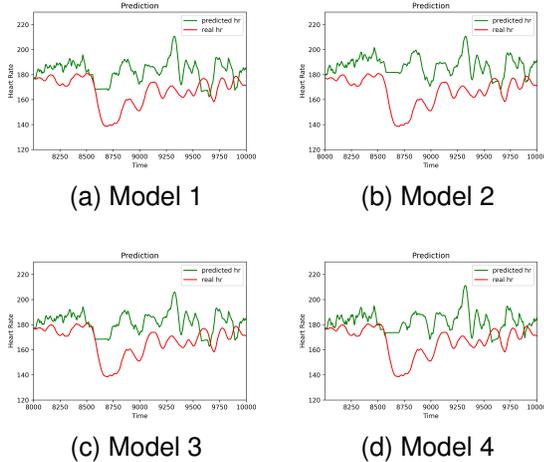


Fig. 4: Heart Rate Forecasting of FFNN Models

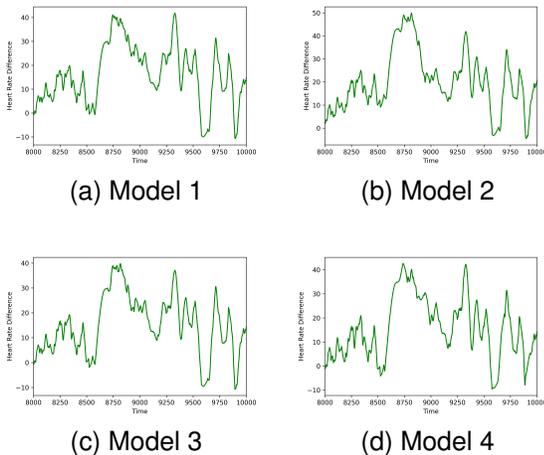


Fig. 5: Heart Rate Forecasting Error of FFNN Models

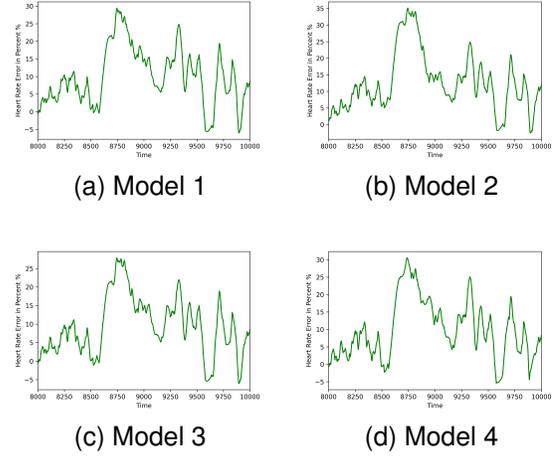


Fig. 6: Heart Rate Forecasting Error in Percent of FFNN Models

Model Number	MSE on Training Set	MSE on Test Set
1	242.89	405.11
2	238.81	568.08
3	262.47	364.91
4	233.25	402.34

TABLE VI: MSE of FFNN models

Compared with random forest models, the variances of FFNN models on the training set and test set are much closer, indicating less overfitting severity. We therefore expect the FFNN models to generalize better than the random forest model because they do not incur such severe overfitting.

C. The Simple RNN Model

Unlike FFNNs, recurrent neural networks (RNNs) can utilize heart rate data in the past to forecast the heart rate at the current moment. Figure 7 shows the architecture of a simple RNN model for heart rate forecasting. The number of simple

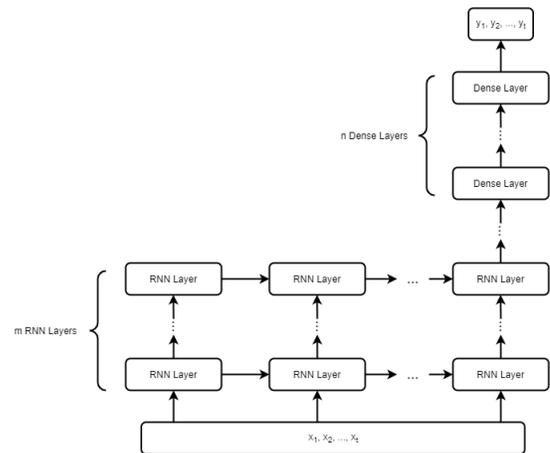


Fig. 7: Structure of Simple RNN Heart Rate Forecasting Model

RNN layers, m , and the number of fully connected layers (also known as dense layers) n , are two important hyper-parameters

in a simple RNN heart rate forecasting model. The heart rate sequence is divided by the maximum heart rate.

Simple RNN Models with different hyper parameters were built and their hyper-parameters are listed in Table VII. The

Model Number	#Dense Layers	#Simple RNN Layers
1	1	1
2	1	2
3	2	1
4	2	2

TABLE VII: Hyper-parameters of Simple RNN models

optimal start learning rates were identified via Smith’s method and an exponential decay learning rate function was utilized for learning rate searching. The learning rate vs loss curves are plotted in Figure 8. From the learning rate vs loss curves

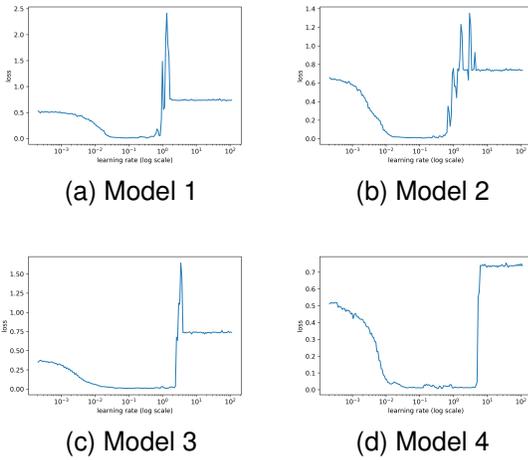


Fig. 8: Learning Rate Search for Simple RNN Models

shown in Figure 8, the optimal start learning rate was selected as 2×10^{-1} .

Table VIII shows the MSEs of four simple RNN models with different sets of hyper-parameters on the training set and test set. For Model 3, the MSE on the test set is much larger

Model Number	MSE on Training Set	MSE on Test Set
1	275.11	248.83
2	628.48	237.68
3	210.31	655.18
4	1245.66	964.61

TABLE VIII: MSE of Simple RNN models

than that on the training set, which indicates overfitting.

The heart rate of the athlete is predicted in Figure 9 and the error and error in percentage are shown in Figures 10 and 11.

Compared with FFNN models, simple RNN Models 1 and 3 exhibit fewer errors and the forecasting results are closer to the real heart rate sequence.

D. The LSTM Model

Simple RNN models can suffer from vanishing gradient problems, which limits their application when the sequence of input data items is very long. To address this issue, therefore,

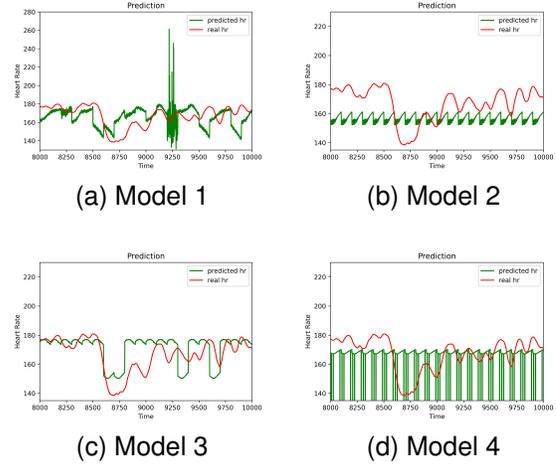


Fig. 9: Heart Rate Forecasting of Simple RNN Models

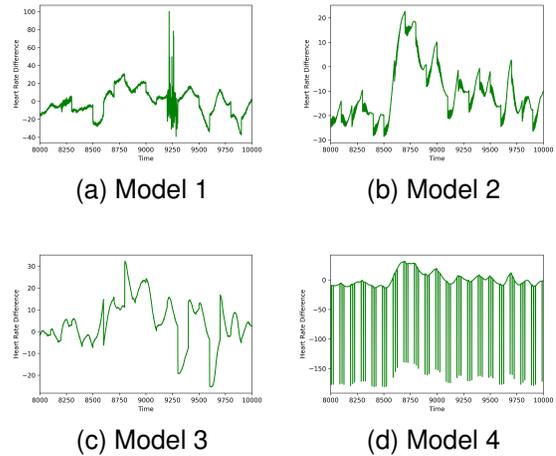


Fig. 10: Heart Rate Forecasting Error of Simple RNN Models

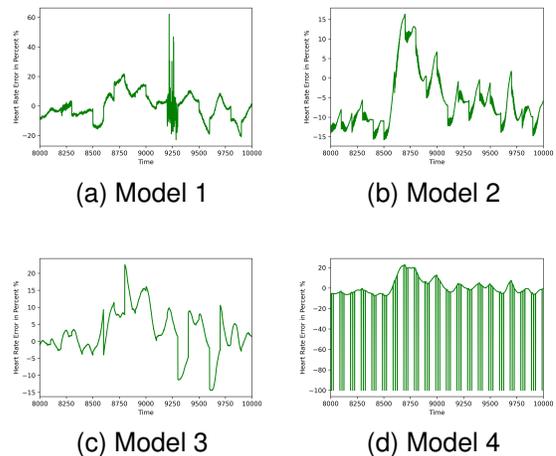


Fig. 11: Heart Rate Forecasting Error in Percent of Simple RNN Models

we also implemented LSTM models. The hyper-parameters of these models are shown in Table IX. The error of the results

Model Number	#Dense Layers	#LSTM Layers
1	1	1
2	1	2
3	2	1
4	2	2

TABLE IX: Hyper-parameters of LSTM models

for two-layer LSTM models is large, which likely occurs since models with two LSTM layers are so deep that our current dataset is insufficient to train them.

The learning rate vs loss function curves that utilize the optimal learning rate finder are shown in Figure 12. The optimal start learning rate for models with only one LSTM layer (i.e., Models 1 and 3) is 1×10^{-1} and the optimal start learning rate for models with two LSTM layers (Models 2 and 4) is 1×10^1 .

The results for the four LSTM models with different hyper-parameters are shown in Figure 13. The heart rate error and error in percentage are shown in Figures 14 and 15, respectively.

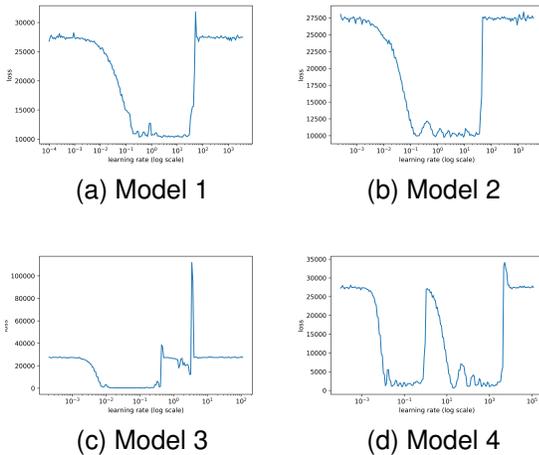


Fig. 12: Learning Rate Search for LSTM Models

The MSE on the training set and test set is shown in Table X. As shown in this table, the models with two LSTM layers

Model Number	MSE on Training Set	MSE on Test Set
1	141.17	200.50
2	1240.60	1015.87
3	62.47	196.61
4	1480.36	1470.36

TABLE X: MSE of LSTM models

exhibit large MSE over both the training set and test set. This larger error may occur since our dataset is insufficient to train a neural network with two LSTM layers. This result may also indicate that the simple one-dimensional signals of speed, position, and cadence are insufficient to learn course-specific heart rate variation.

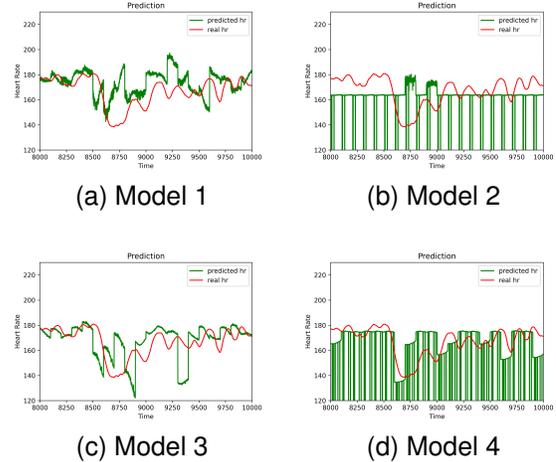


Fig. 13: Heart Rate Forecasting of LSTM Models

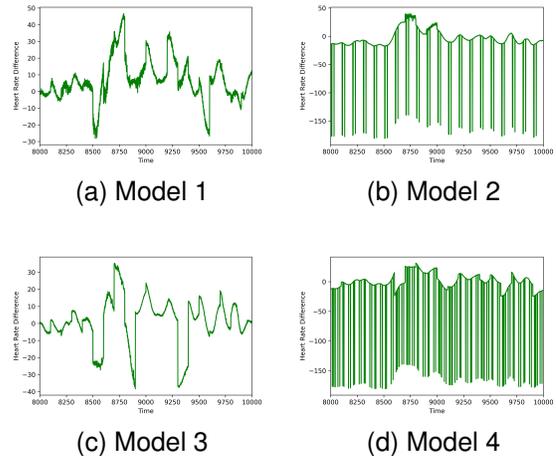


Fig. 14: Heart Rate Forecasting Error of LSTM Models

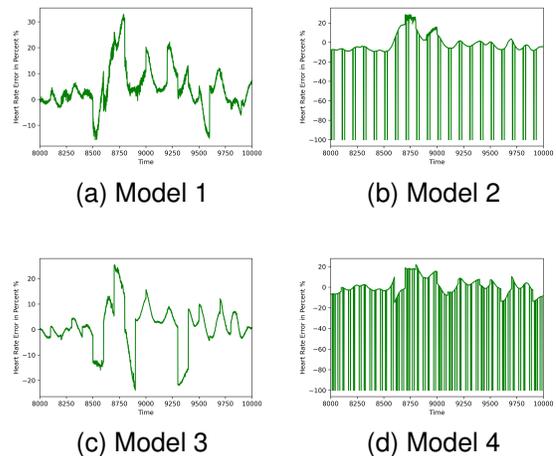


Fig. 15: Heart Rate Forecasting Error in Percent of LSTM Models

E. Comparison with Other Heart Rate Models

Based on the results presented above, it appears that two LSTM models with only one LSTM layer perform better than the other three types of model. We therefore also compared these LSTM models with Luo’s LSTM model [9] and Ni’s LSTM-based model [8], which are course-independent and rely only on personalized factors and contextual factors. The input features to these latter two models were cadence, speed, altitude, and time.

Since Luo and Ni’s models are not course-specific, the grade of a biking course is excluded in the input factors. In particular, only the structure of their models are utilized and some layers (such as the encoding layers in Ni’s model) are removed since heart rate forecasting is the main focus. The structure of these models are shown in Table XI.

Models	Layer Structure of Heart Rate Forecasting Model
Ni’s model	LSTM + Dense + Dropout
Luo’s model	LSTM + Dropout + LSTM + Dropout
LSTM model 1	LSTM + Dense
LSTM model 3	LSTM + Dense + Dense

TABLE XI: Structure of Heart Rate Forecasting Models

These two models were first trained on the same training set as our heart rate forecasting models with course-specific factors excluded. They were then tested on the same test set. The MSE of all four of these models is shown in Table XII. The forecasted heart rate is shown in Figure 16.

Models	MSE on Training Set	MSE on Test Set
Ni’s model	1822.23	407
Luo’s model	239.89	157.40
LSTM model 1	141.17	200.50
LSTM model 3	62.47	196.61

TABLE XII: MSE of LSTM models

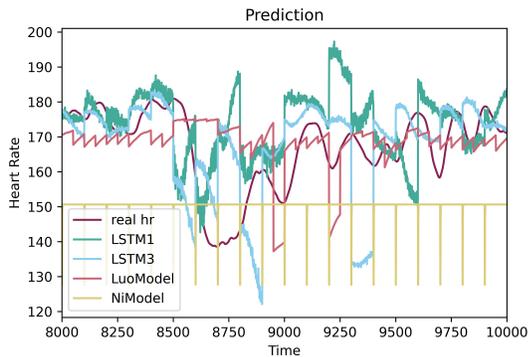


Fig. 16: Comparison of Different Heart Rate Forecasting Models

While Ni et al.’s model showed less error on both the training set and test set, the heart rate it forecasted is close to constant except for several drop outs. Luo et al.’s model captures the heart rate pattern at around 170 beats per minute, but cannot follow the heart rate pattern overall.

V. SUMMARY OF OUR EXPERIMENT RESULTS

This section summarizes the results from our experiments in Section IV.

A. Summary of Random Forest Model Results

The random forest models presented in Section IV-A exhibit severe overfitting, likely because these models are based on decisions from an ensemble of tree regressors, which are data sensitive. In particular, tiny fluctuations in the input sequence can result in dramatically different outputs. Data fluctuation is common and unavoidable in real-world heart rate forecasting for cycling due to the mechanical vibration and the cyclist’s movement.

The Gini importance analysis shows that random forest models value speed, time, and altitude above grade and cadence, which is responsible for most of the errors. Due to severe overfitting, therefore, random forest models are poorly suited for personalized and course-specific heart rate forecasting in our dataset.

B. Summary of FFNN Model Results

Compared with the random forest models described above, Feed forward neural networks (FFNNs) did not incur overfitting issues. The major error source stems from the time dependency of heart rate, i.e., the heart rate at t -th second depends on what happened in the past (e.g., the cyclist rode up a steep hill). Errors also relate to the heart rate and other factors at $0, 1, \dots, t - 1$ seconds. Due to the nature of FFNNs, however, these models cannot deal with time dependencies efficiently.

C. Summary of the RNN Model Results

We tested two types of RNN models: a simple RNN model and an LSTM model. Our results showed that the simple RNN model captured the main trends of the heart rate sequence. The error source in the RNN models stemmed from either gradient vanishing or a gradient explosion, as described below:

- Gradient vanishing occurs in a long sequence, when the output value is large. In this case, the gradient of the RNN’s sigmoid activation function is close to zero, leading to slow or no update to the weight matrices and bias vectors [24].
- Gradient explosion occurs when an RNN is learning a long sequence and the gradient rises sharply, resulting in an unstable neural network.

These two problems may be the error source for simple RNN models, depending on sequence size.

In all four types of models, LSTM models show decent performance without severe overfitting. The LSTM has three gates that reduce the likelihood of vanishing or exploding gradients. For both simple RNN and LSTM models, however, models with two RNN/LSTM layers perform poorly since these two layer models are too deep to train efficiently with our dataset.

D. Mapping Our Results Onto Research Questions 1, 2, and 3

For research question 1 in Section III-A both course-independent models do not capture the heart rate trend of the cyclist well from 8,000s to 10,000s, as discussed in Section IV-E. In particular, the LSTM model proposed by Ni et al. [8] mainly outputs a rectangular heart rate sequence due to the lack of course-specific factors, such as grade. Ni et al. [8] state that their model focuses primarily on short-term predictions (typically in a window of 10 seconds), so a 2,000-second sequence may be too long for their model. Luo's model forecasted a somewhat continuous heart rate around 170 beats per minute with small dips around 9000s and 9250s. In general, our results show that these two models are not as accurate as our LSTM models since they do not consider course-specific factors.

For research question 2 in Section III-A, random forest models exhibit lower MSE on the dataset, but their substantial difference in MSE on the training set and test set indicates that they all incur severe overfitting. The maximum depth of each decision tree regressor in random forest models are all over six times the number of factors, which means that RF model split some factors over six times. This splitting dramatically increases the complexity of the forecasting models and can result in severe overfitting.

Moreover, as the data size grows larger, the depth of the decision tree regressors also grows because the output decision tree regressor will cover all the heart rate cases, including any erroneous data in the dataset (e.g., due to sensor noise during collection). As the data set grows larger, the number of erroneous readings will unavoidably increase, thereby increasing the probability of erroneous prediction due to the accumulated influence of error. As a result, conventional machine learning models have difficulty on course-specific heart rate forecasting.

For research question 3 in Section III-A speed has the highest Gini importance, which aligns with prior work on heart rates for cyclists [5] and is utilized as the splitting factor for the first layer. The three major factors are speed, time, and altitude. In contrast, the influence of cadence and grade are considered less important in decision tree construction.

In summary, our LSTM Models 1 and 3 do not suffer from overfitting and offer reasonable heart rate forecasting. Compared with course-independent models, the forecasted heart rate of our course-specific models are closer to the real-world heart rate sequence.

VI. CONCLUDING REMARKS

This paper presents an empirical analysis of personalized and course-specific models to forecast heart rates for cyclists. In particular, we explored the performance and feasibility of learning a cyclist's course-specific heart rate model from a single ride on a given course. We implemented models using long short term memory (LSTM), recursive neural network (RNN), random forest, and previously published architectures and compared their performance learning a cyclist. We also compared our model with Ni et al's [8] and Luo et al.'s [9] models.

The following are key lessons learned from our research on single-ride personalized and course-specific heart rate forecasting in cycling:

- **Overfitting is a challenge for traditional machine learning models.** Our MSE analysis in Section IV-A showed the random forest models had severe overfitting, due to the effect of erroneous data (e.g., noise in commodity sensors) in the training set. Likewise, as the data set grew, erroneous readings introduced poor performance in the random forest forecasting models.
- **Course-specific factors are crucial in heart rate forecasting.** In Section III-D, the Spearman's correlation coefficient showed that the grade of the course (which is a course-specific factor) was highly correlated with heart rate. Moreover, Section IV-E showed that two course-independent models captured heart rate patterns poorly compared with our course-specific LSTM models.
- **Course-specific models offer accurate heart rate forecasting.** The results from our comparisons indicated that our LSTM-based models exhibit slightly lower mean square error (MSE) and mean absolute percentage error (MAPE) compared with Luo et al.'s model. Likewise, Jianmu Ni et al's model does not offer reasonable heart rate forecasting on the given dataset compared with our LSTM-based models.
- **Personalized and course-specific LSTM models can be learned for a cyclist to forecast heart rate from a single ride of a course.** More work is needed to validate this observation, but our initial results are promising. The heart rate forecasting results in Section IV showed that the accuracy of the LSTM models outperformed the other two neural network models and did not have as severe overfitting as the random forest models. In Section IV-E, the LSTM course-specific models also performed better than the two LSTM-based course-independent models.

Our future work focuses on scaling up our validation on a larger body of cyclists to determine whether these results hold true across a range of riders. We are also exploring how imagery of the course can aid in understanding complicated course features, such as terrain roughness. For personalized factors, we are evaluating the extent to which learned course-specific models transfer to other riders of the same gender and age, as well as bike types. We are also considering dynamic personalized factors, such as breathing rate.

For course-specific factors, image data and videos are being collected and analyzed via neural networks. The roughness and course conditions at different parts of the course are being analyzed from these images and applied in our heart rate forecasting model.

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