Cardiovascular Fitness Recommendations

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Abstract

Cardiovascular disorders are one of the prevalent causes of acute fatalities in sportspersons. Regular physical activity helps maintain cardiovascular fitness and lowers the risk of cardiac disease. However, under intense physical exertion, a sportsperson may succumb to sudden cardiac death. People, with the evolution of intelligent devices, have the opportunity to track and measure their heart rate during physical activities. That's why data collected from these devices is a promising source. Though it is challenging to model such data because this kind of data has a high level of heterogeneity, diversity in scale, and complex interdependencies. Therefore, it is necessary to handle such data using some machine learning approaches for personalized recommendations. Specifically, this work focuses on the prediction of the heart rate of the user for the next moment. We have designed a model that can learn the heart rate profile of the user during exercise and can predict the short-term profile of heart rate so that users can effectively manage the maximum or minimum heart rate. Here, a Long Short Term Memory based model with dual attention has been used to predict the heart rate for the next moment of a user.

Keywords: Cardiovascular Fitness Recommendations, personalised recommendations.

1. Introduction

Living a sedentary and poor lifestyle is one of the major causes of numerous health problems. But in recent years, humans have developed technology in the form of wearable devices that have given us the ability to keep track of daily activities by only wearing smart bands or by just carrying our mobile phones. With this, we can measure various activities such as heart rate, location, altitude, activity type, calories burnt ,and much more. This type of sequential data can be harnessed for a lot of useful information and can predict heart rate and other parameters, but the collected data is often heterogeneous and consist of interdependencies that are hard to capture. Another reason is the changing activity patterns and the health fluctuation of the user. Also, data has high variance from user to user. This type of data can easily be calculated, whereas getting lots of data about a particular user is far more complicated than the former. Our target is to adopt a model to capture features in workouts or activities done by the user. We propose a method based on the Recurrent Neural Network [1], [2] model to capture gathered sequential data, which has shown significant performance [3]. An extensive dataset of activities is explored in order to build a predictive model. Here, the suggested model is based on LSTM, which takes attributes of the person and several session parameters. The model can be used to predict (1) Quantitative tasks, such as predicting workout parameters that will change simultaneously as the session goes ahead; (2) Qualitative metrics, like finding significant features that affect performance more in comparison to others.

1.1. Motivation

The impact of the famous quote 'health is wealth' on people is increasing tremendously. Below are some points behind motivation.

- Health is the foremost requirement for doing anything. If we are unhealthy means losing out precious time from our life for getting treatment and lacking energy and confidence in every task we do.
- Campaigns like International Yoga Day, Swastha Bharat, etc., also add to our motivation (motivate people to stay healthy).
- The spread of new diseases like COVID-19 can only be tackled with a sound immunity system. Further, people with cardiovascular diseases are more vulnerable to these diseases, and that's why we use heart rate profile forecasting and prediction for the short term.
- Due to such a busy life, we tend to do a good workout in limited time and also acc to our health factors.

Therefore, this work will help users to predict their workout profile (speed and heart rate) and also suggest workouts for better immunity in individuals. The overall contribution of this work is summarized as follows:

- To study different techniques/algorithms and find the best one based on accuracy.
- To provide the personalized prediction of the workout profile (speed and heart rate) of a user.
- Implement the model in real-time by giving a prediction for the short term.

2. LITERATURE REVIEW

Table 1 summarizes a few different paradigms associated with fitness recommendations. In particular, each paradigm's methodology has been illustrated using some representative research articles. Further, we have listed a few limitations, in terms of the pros and cons, of these techniques.

Table 1: Different methods for fitness recommendations

Paradigm	Brief Methodology	Pros	Cons
Mining Sensor Data. [4][5][6]	This category falls into pervasive computing and studies about the collection and handling of data from wearable and mobile devices like smartwatches and fitness bands. Here data can be related to the various types of behaviour of a person like sleep order, health, exercise and many more. To model a person's wellness by using some sensor data is a present-day growing trend.	Users' exercise data can be collected easily and can be combined with social network details/statistics to forecast his/her fitness trends [7]. Limited training data can be used to detect exercise types like walking, running, aerobics, etc. [7] specifically focused on the Body Mass Index (BMI) for the same.	Prediction and recommendation tasks are not satisfactory as they are not using sequence prediction (sequential modelling).

Context-aware modelling.[8][9]	A system or its components can collect information about its environment at any given time and accordingly adapt behaviours; this is known as context awareness. Fitness and exercise data have heterogeneity in the input structure naturally (contextual data and sequential information), and hence context-aware modelling can be used.	Recommender systems, clinical predictions, social networks with contextual information, etc., are some of the applications which can be fulfilled by context-aware modelling. RNN models can be used with the context-aware layer [8].	An LSTM layer with contextual embedding modules performs better than context-aware modelling as it also learns from historical sequences. Measurement within each activity does not consider in context-aware modelling.
RNN-based sequential modelling.[10][11]	RNN (Recurrent Neural Networks) recently has shown exceptional efficacy in modelling sequential data such as clinical data, text, and audio. These are a type of neural network where the input to the current unit is fed through the output of the previous unit along with the new input of the current unit.	RNN-based models can be combined with convolution layers (CNN) to show short as well as long-term dependencies both. This model performs better than Linear SVM and other RNNs.	Measurement within each activity does not consider in RNN-based sequential modelling.
Personalized Recommendation.[7][12]	User behaviour is a crucial point of personalized recommendations. Also, these are based on a large amount of historical data of the user and then recommend some products in static scenarios like e-commerce. Personalized recommendations incorporate content like item attributes and contexts like user clicks or purchases. Now, researchers from these industries are trying to evolve such systems for personalized recommendations.	Various targets, such as user's goals, desirable performance and environment, can be considered for personalized running route recommendations [12]. A combination of workout information and social network information can be used to conduct wellness predictions [9].	These works don't centre around the modelling of sequential fitness data like the heart rate/speed sequences of a user. A few works in personalised recommendation provide hand-crafted statistics instead of providing the whole sequential information of each activity/task.

3. BACKGROUND

3.1. *Recurrent Neural Network(RNN)*

It is a general feedforward neural network with internal memory. RNN performs the identical function for each input of data, and that's why recurrent in nature. The current input's result relies on the previous unit computation. The output is copied after producing from the previous step and then sent back into the recurrent network. These are gaining popularity in today's world very drastically from advances in network designs and also by increasing the computational power of Tensor Processing Unit (TPU) and Graphic processing units(GPU). These networks give the best result in the case of sequential data because the RNN unit is easily able to maintain information about the previous unit result by using its internal memory. To process the sequence of data, RNNs can use internal memory, which distinguishes RNNs from feedforward neural networks. That's why, with all these features, tasks such as handwriting recognition, speech recognition, time series prediction etc., can be easily performed by RNN. Unlike other neural networks, all the inputs are related to each other in RNNs.

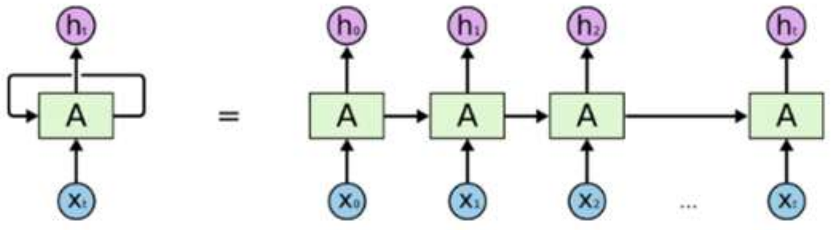

Figure 1. Unfold Recurrent Neural Network

The drawback of the RNN is that it can't be used with a very long sequence, and it has a problem of vanishing gradient. Also, it is a very difficult task to train an RNN. In figure 1, Xt is an input, A is an activation function, and ht is the output corresponding to each cell.

3.2. Long Short Term Memory (LSTM)

The LSTM has an architecture similar to the RNN, but it has overcome the limitations of RNN (like it is fully capable of remembering the past values of the context). These values will not change over the entire training period of the model. Basically, an LSTM contains four components, which are LSTM Recurrent Components, Gates, Blocks, and LSTM units. LSTM units are capable of storing the values for short as well as for a long time. An LSTM Block contains a lot of similar units. LSTMs come under deep neural networks. So, well known for their better results. LSTMs are implemented in parallel/stacked systems to minimize the workload of large-scale computing systems. To control the overall flow of information, LSTM has three gates. Different logistic functions are used for implementing these gates, for having a result between 0 and 1. The name of the gates are Output gate, Input gate and Forget gate. For the entry of information inside or outside the memory, these logistic functions are multiplied. The input gate plays a pivotal role in controlling the entry of new values into memory. The Forget gate controls the amount of time till a value will remain inside of memory. We can forget the old value when a new value is available. This functionality is controlled by the update gate. The combining effects of input and forget gates are represented by the update gate. Following is the basic information of all the gates of a Long short term memory (LSTM) unit.

- Input gate – input gate plays a pivotal role in controlling the entry of new values into memory. Through [0,1], which values to enter, are decided by a sigmoid function. Further, these values pass through a tanh function to determine their significance ([-1,1]).
- Forget gate – It discovers the details which need to be abducted from the unit. This is done using a sigmoid function or some other activation function. A number between 0 and 1 is given as output (i.e. omit this or keep this).
- Output gate – This gate is used to decide the output. Like the input gate, here also through [0,1], which values to enter, are decided by a sigmoid function. Further, these values pass through a tanh function to determine their significance ([-1,1]).

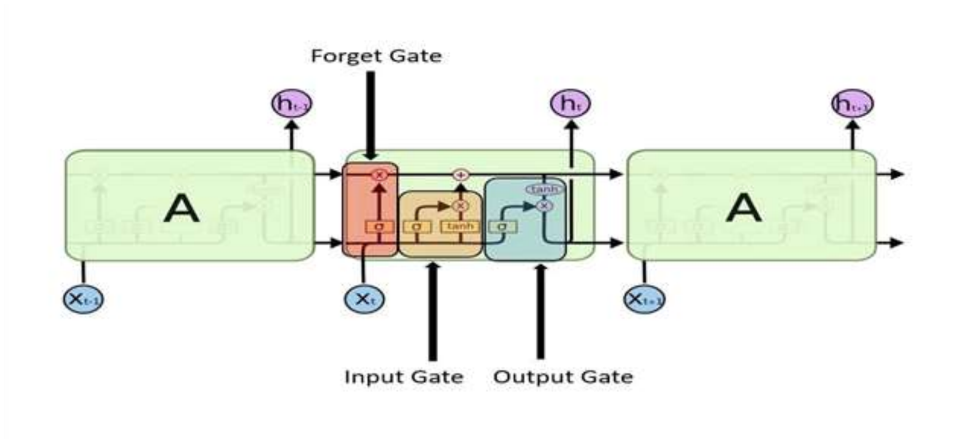

Figure 2. Typical DataCenter Infrastructure [18, 19]

4. PROPOSED APPROACH

We have taken two kinds of sequential data problems, i.e., prediction for the short term and prediction of workout profile [13].

Prediction of workout profile: This module takes contextual sequences, attributes of a user's workout, historical sequences, and the total time of a workout and predicts the target. This task can be considered as a case when the user has given his intended route and desired the whole time, i.e., how much the user wants to perform the intended task so that the system predicts or forecast what would be the heart rate profile of the user.

Prediction for the short term: This module takes contextual sequences, attributes of a user's workout, historical sequences, along with total duration. These inputs can be referred to as estimates for a particular period of time corresponding to a fixed duration of a single activity session. This allows us to predict the heart rate for a short term during the activity session.

The interrelationship between tasks: Basically, both the tasks differ in inputs and outputs and application scenarios. Short term prediction module aims to predict sequential parameters during the activity session. It is like traditional time-based models used to predict the parameters at a particular instant of time. This is useful in cases of anomaly detection and real-time prediction; e.g., this can advise the user to slow down the pace of a workout in case his heart rate is going to exceed the next moment.

Whereas predicting of workout profile module aims to predict the performance of the user on being provided route and time as input. It will predict trends for a complete session like maxima, minima and average of the parameter, i.e., heart rate, and it also predicts the speed of the workout in the same manner before the user starts doing the activity. From this model, the user can formulate his plan for the workout that can meet his expectations, i.e., how many calories she/he wants to burn and also judge if the workout is according to the ability of his body or not. Moreover, the model helps to formulate a plan which is according to her/his expectations of performance, and it can also be used to find alternate routes for the workout. In other words, this model can predict a few suggestions, and the user can check these against his/her expectation.

4.1. Modules Split-Up

Figure 4.1 depicts the overall architecture of the system along with the different modules, and a sequence of data flow is shown in Figure 4.2.

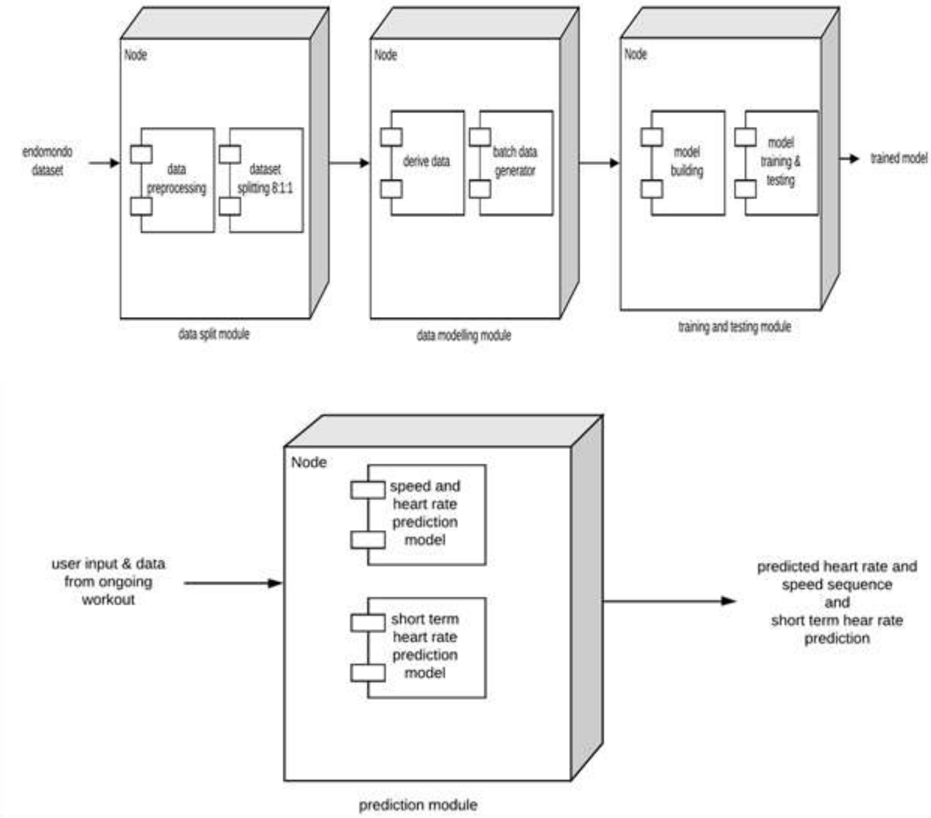

Figure 3. System Architecture of the proposed approach

- Data Split Module – This module does preprocessing and test train splitting of data. After that, data is in a usable form.
- Data Modeling module – This module derives some additional attributes like distance, speed, etc., for dividing the whole dataset into batches of small size.
- Training and testing module – Here, we apply LSTM to train and test our model and finally get the trained model.
- Prediction Module – This module takes inputs like route as the sequence of longitude, latitude and altitude, time etc. and predicts the heart rate and speed and also makes predictions for the short term.

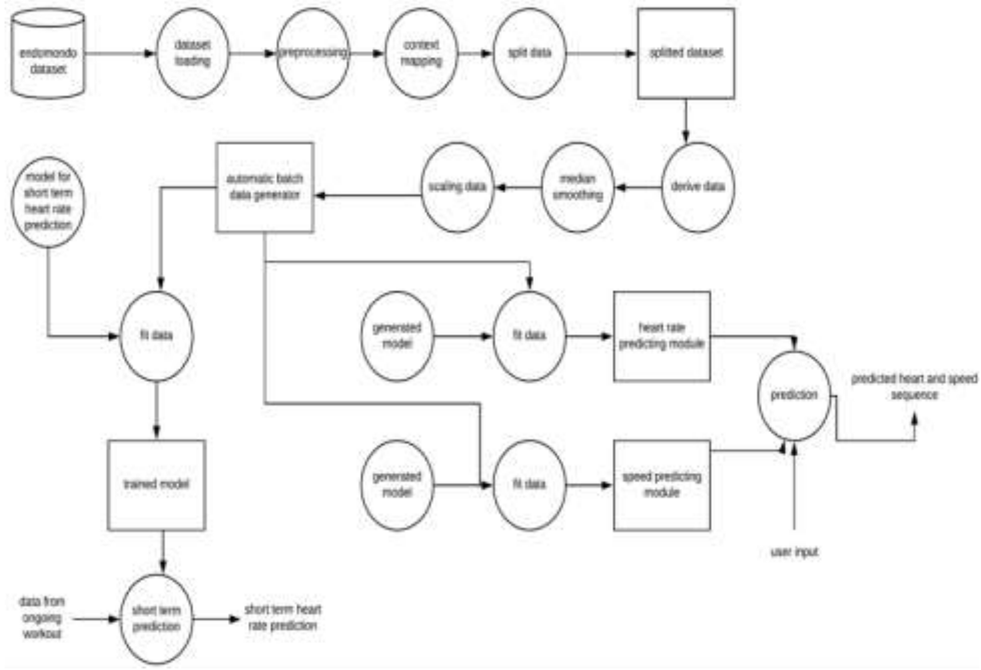

Figure 4. The flow of data in the system

5. Experiments & Results

The experiments are designed to forecast the profiles of workouts, i.e., the speed and heart rate profile of the user. A user can use this profile forecast to find a workout plan which can meet the expectation of the user on performing a particular task. Further, prediction for the short term will be helpful to detect any kind of anomaly in his/her heart rate and also helpful for real-time decision making. For example, the user can be advised that he/she ought to slow down in the next moment so that his/her heart rate will not exceed the maximum desired rate.

5.1. Dataset

The dataset from a popular website called endomodo.com [13] is used for all the experiments. The dataset consists of measurements and contextual data. Measurements include 1)timestamps 2)heart rate 3)speed 4)distance and contextual data include 1)latitude 2) longitude 3)gender 4) altitude 5)user 6) sport 7)user identity.

The dataset has a massive missing rate since not all devices like smart bands provide all the attributes mentioned above, and that's why we preprocess the data and add a few derived attributes like distance and derived speed for training our model. The dataset contains more than 2,00,000 records of workouts spread across more than 900 users.

5.2. Workout Profile Forecasting

Due to the large dataset and each instance of the dataset containing a huge amount of continuous sequential data having altitude, longitude, latitude, timestamps, heartbeat, and data from other sensors, we took a slice of 15000 workout records of 90 unique users. Firstly, we partitioned the dataset into training, testing, and validation sets into the ratio of 8:1:1. We have used 50 epoch/iterations to train the model for heart rate prediction, and the score(loss) decreased from 10364.802 to 259.49. Table 2 shows the details of the best scores for workout profile forecasting.

Table 2. Scores And Errors In Workout Profile Forecasting

Profile	Dataset (Training/Testing)	Best Score	Mean Absolute Error(MAE)	Root Mean Squared Error(RMSE)
Heart Rate	Training	259.49	12.95	17.216
	Testing	291.96	12.98	16.82
Speed	Training	15.89	2.73	4.40
	Testing	25.39	2.62	5.104

The score can further be improved by increasing the number of epochs/iterations, as shown in Figure 5.

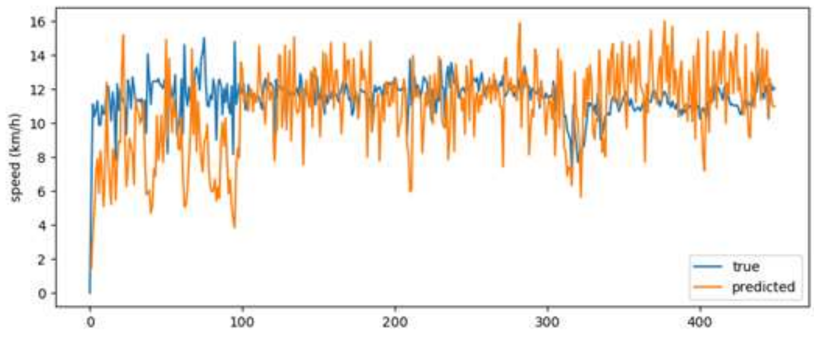

Figure 5. Speed Profile Forecasting

5.3. The Prediction of Short-Term

As shown in Figure 5.2, it is clearly visible that with an increasing number of iterations, the loss reduces significantly up to a point.

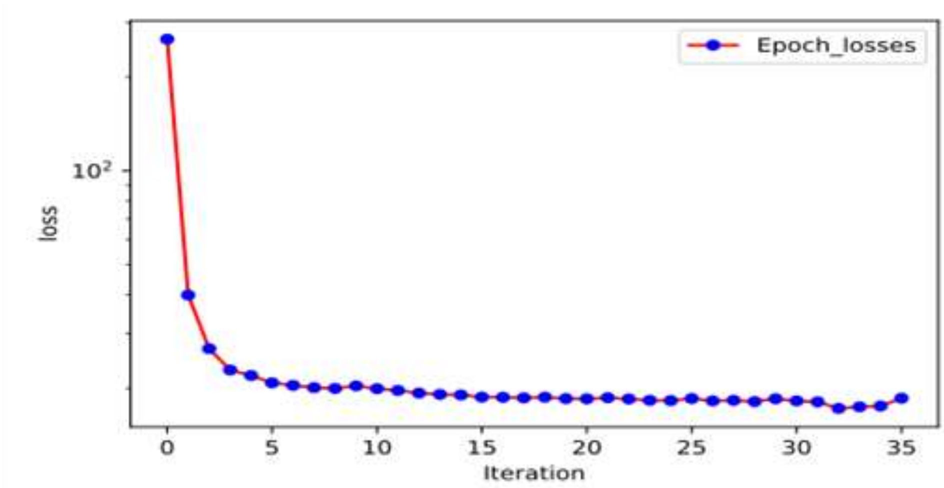

Figure 6. Iteration v/s Loss for prediction of short term

Further, the prediction of short-term heart rate (in BPM) is evaluated against the number of epochs/iterations. Results in Figure 7 show promising values for a sports person's short-term prediction of heart rate and can be used in real-time for decision-making.

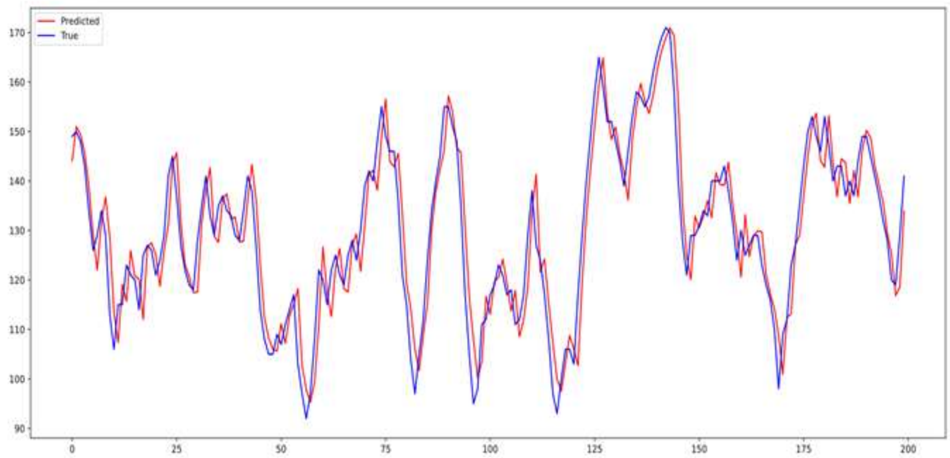

Figure 7. Prediction of short-term Heart rate(real-time)

6. Conclusion And Future Work

We have presented a system that solves problems of sequential forecasting in exercising and fitness-related data and can be used as an elementary unit for improving personalized fitness recommendation applications. From the supplementary information like user ID, sport/activity type and historical sequences of the workout, embedded description/presentation can be learned. Each of this embedded information is comprised of a sequential modelling framework (Long short-term memory) to achieve high accuracy of prediction.

We have tried to provide very high-quality predictions (short-term predictions) with promising results. Furthermore, interactive recommendations and some other recommendations like route recommendations (which fulfilled the user performance preferences and goals) can also be implemented by further studies.

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