DeepRace: GRU-Based Sequence Modeling Framework for Marathon Performance Prediction

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In recent years, data-driven approaches have gained prominence in sports analytics, offering new opportunities for optimizing athletic performance. This study presents DeepRace, a computational framework based on deep learning models including Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU) for marathon performance prediction. Using a dataset of 23,763 training activities from 549 athletes who participated in the 2017 Boston Marathon, we evaluated the effectiveness of sequence-based models in forecasting marathon finish times. The framework systematically preprocesses and analyzes sequential workout data, employing a multi-model selection algorithm to identify the most accurate predictive model. Experimental results demonstrate that the GRU model achieved superior performance, with a Mean Absolute Percentage Error (MAPE) of 5.2 percent and a Root Mean Squared Error (RMSE) of 0.11 hours, outperforming both RNN (MAPE 5.6 %) and LSTM (MAPE 6.5 percent) models. Notably, all deep learning models significantly surpassed the baseline linear regression model (MAPE 10%), confirming the advantage of deep learning for time-series performance prediction. These findings underscore the potential of GRU-based sequence modeling for enhancing marathon training strategies, offering actionable insights for athletes and coaches aiming to improve race outcomes through data-informed decisions.

Povzetek: Avtorji predstavijo DeepRace, GRU-temeljen napovedni model za maratonski čas, ki na osnovi treningov natančneje napove rezultate tekačev kot RNN, LSTM ali linearna regresija.

1 Introduction

Over the last decade, endurance sports have increased significantly and drawn individuals from around the globe. The finishing rate in ultra-long running competitions has risen by over 40%, while the popularity and competitiveness of these events continue to grow [1]. This, therefore, calls for the need to prepare athletes for them to execute their best during national and international tournaments. Good planning of workouts and training regimes is an important part of effective preparation; it is considered crucial to enhancing performance. Yet, there are limited well-structured studies or consistent research into evaluating performance in athletes before competitions. Even with advancements in technology and data analytics, few applications can be found for such technology in predicting and analyzing athletic performance, especially for endurance sports.

Various physiological and environmental factors come into play in defining the performance of track athletes in any race. Complications such as dehydration, cramped muscles, overexertion, or even pacing are very critical. For instance, an excessively fast start as compared to your training preparation results in an early onset of fatigue, inappropriate hydration strategies result in reduced endurance capabilities. These will require an in-depth cause knowledge and also how they interact. Precise performance predictions could enable athletes to optimize their training routines, refine strategies, and improve race outcomes. This gap motivated us to explore predictive models that can effectively assess and forecast the performance of athletes with precision.

This research will try to find answers to the following important questions: Can deep learning models give more accurate results for the performance prediction of athletes in competition? What are the most influential parameters and metrics for athletic outcomes? Which practices in workouts yield the best results regarding performance optimization? Guided by these questions, this paper outlines a research study that proposes the development of a predictive framework that is capable of analyzing training regimens to make informed decisions to improve the competitive readiness of athletes. To address this, we present a model designed to forecast athlete performance in preparation for significant competitions. Indeed, accurate predictions of performance will have a great impact not only on competition outcomes but also on guiding athletes to make informed adjustments to training and lifestyle. This work will explore several deep learning methods, including including Recurrent Neural Networks (RNN) [2], Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU), in determining the best approach for the work at hand. Though RNNs are good to go for processing data in a sequence and considering temporal dependencies, they provide a good basis for time-series analysis, but their capability to handle long-term dependencies is restricted because of issues with vanishing gradients [3]. LSTMs overcome this issue by incorporating memory cells into their architecture that can retain information across long sequences, performing exemplary in the task of prediction and classification on sequential data [4]. GRUs, on other hand, are similar but more lightweight versions of the LSTMs, providing advantages of LSTMs with reduced computational complexity, hence faster to train.

Table 1 Overview of literature focused on athlete marathon race time prediction

Reference	Year	Race Classification	Forecast Objective	Number of Participants	Variables Examined
[14]	1983	Long-Distance Run	Timing Forecast for Races	19	Velocity calculated at the anaerobic boundary
[15]	2012	Ultra-Distance Run	Aggregate Distance Covered over a One day	64	Longest workout durations, total distance run, and individual best marathon results
[16]	2011	Half Marathon	Estimating Race Times	84	Age, body measurements (e.g., BMI, limb circumference), and experience as an active runner
[17]	2014	Half Marathon	Predicting Race Times	230	Running speed, body composition (e.g., skinfold thickness, BMI, body fat percentage)
[18]	2013	Full & Half Marathon	Statistical Analysis (No Prediction)	147 & 126	Age, body size (e.g., height, BMI, limb circumference), weekly running distance, and total training hours
[19]	2017	Half Marathon	Evaluating Race Performance	78	VO2 Max, speed at anaerobic threshold, step rate, step length, peak speed, flight/contact times
[20]	2019	Full Marathon	Assessing Race Performance	16	Aerobic and anaerobic thresholds, maximal oxygen capacity, and running effectiveness

2 Literature review

This section revisits various methods that have been proposed in the literature for predicting athlete performance. Although few studies on this topic exist, there have been several related efforts with respect to race time prediction using historical training activities and the physical characteristics of athletes.

The work by Vickers et al. [7] employed the Riegel formula for race time estimation up to the half-marathon distance. Reasonable performance was demonstrated. These models, however, underestimated the race times by 10 minutes for 50% of the dataset used for building these models that had been collected through an online survey. The variables studied were age, sex, body mass index, training programs, and mean race velocity. A second model was also analyzed that focused on 22 runners running 46 races and doing an 8-week training program. These correlations, using the mathematical techniques of correlation, between the weekly training distances, average training pace, and race performance were considerable as stated in this study [8].

Further research has utilized a multivariate analytical approach to test interactions that existed between athlete characteristics and training parameters [9]. For instance, body mass, height, BMI, and circumferences of limbs were combined with the training variables of speed and volume. The results showed that the lower calf circumference and higher running speed at training were the best predictors of race performance improvement. Besides, a seventh-degree polynomial regression model was used to predict the sprint times of Olympic athletes based on more than a century of historical data. This model was most successful for short races [10].

Prominent international marathons, like the Boston and London marathons, serve as valuable data sources for research on predictions of performance. For example, one of the studies used data from the 2015 versions of these marathons, considering variables such as distance, time,

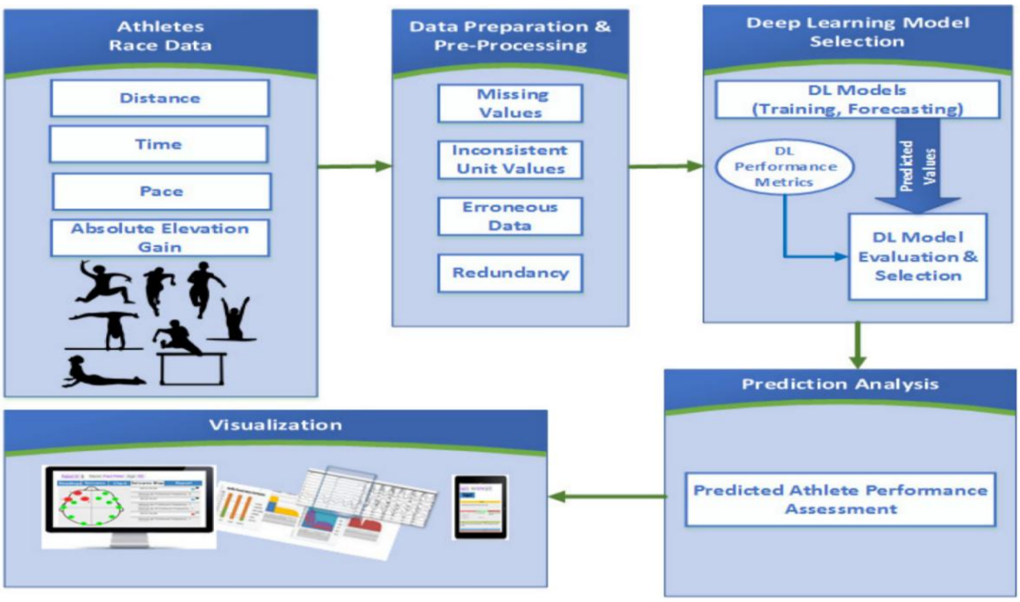


Figure 1: Optimized deep learning framework for predicting athlete performance.

net elevation gain, and workout pace [11]. The outcome indicated that the ensemble learning methods, such as bagging algorithms, were superior to linear regression in predicting the race times of amateur runners. Another study [12], on the other hand, utilized data from Strava, including metrics such as pace, heart rate, and cadence. With the help of the automated feature extraction tool tsfresh, personalized race strategies are developed for each athlete to open new avenues towards improvement by data-driven methods.

A summary of studies focused on marathon race time predictions is provided in Table 1, which outlines dataset sizes, predictive variables, marathon types, and target metrics. A common limitation across these studies is the relatively small dataset sizes, which constrain the accuracy and generalizability of the models. Furthermore, many studies rely on physiological variables such as Oxygen levels and pulse rate, which are challenging to monitor reliably during training sessions. Although various methodologies have been explored, few works have utilized machine learning techniques for race time prediction. Specifically, one study undertook a case-based reasoning approach to estimate race times [13]. However, no work reviewed has utilized deep learning models for race time prediction. Deep learning holds considerable promise for improving prediction accuracy and managing big datasets with ease. This again indicates that more studies are required to be done on deep learning-based approaches to give more accurate and practical tools for race outcome forecasting to improve the performance of athletes.

2 Methodology

This section elaborates on the proposed deep learning-based algorithm to predict the performance of athletes for future tournaments using their workout data. The main objective of the approach is to contribute to enhancing an athlete's performance through correct forecasting of his/her race time for an upcoming marathon. These predictions can be used to motivate the athletes in maintaining consistency and perfecting their training to realize expected performances. The steps in the approach will be: data collection, data preprocessing, selection of the most appropriate deep learning model, and then the prediction of competition performance using the model. Figure 1 shows the framework that highlights the main modules of the solution. This is supported through the core of two key modules: Multi-Model Selection and Prediction Analysis. Each one interrelates in making predictions valid, as shall be elaborated later in detail.

Algorithm 1 Athlete Race Time Multi-Model Prediction Algorithm

```
Input:
athleteList: List of athletes with their workout sessions, including details
    such as distance, elapsed time, pace, elevation gain, and calories burned.
predictionModels: List of candidate deep learning models for prediction.
Output:
PredictedT: Predicted race finishing time.
selectedModel: Selected deep learning model.
procedure ATHLETERACETIMEMULTIMODELPREDICTION(athleteList,
    predictionModels)
  minMAPE ← ∞
  for each m ∈ predictionModels do
    for each a ∈ athleteList do
      W ← getWorkoutList(a)
      for each w ∈ W do
        t̂ ← Predict(w, m)
        MAPE ← evalMAPE(t̂, w)
      end for
    end for
    if MAPE < minMAPE then
      minMAPE ← MAPE
      PredictedT ← t̂
      selectedModel ← m
    end if
  end for
  return PredictedT, selectedModel
end procedure
```

A) Model Description

The proposed framework identifies the important workout activities and training metrics that are bound to

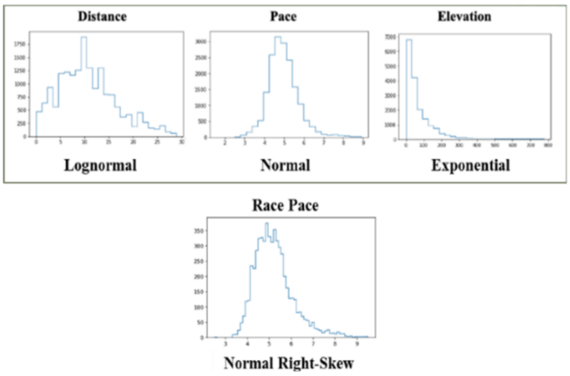


Figure 2: Distribution of training activity data and marathon race paces, showcasing the lognormal distribution of distance, the normal distribution of pace, the exponential distribution of elevation, and the slightly right-skewed normal distribution of marathon race paces.

have the highest impact on optimizing athlete performance. Key metrics are then selected with precision: distance, duration, pace, and elevation gain serve as indicators for training effectiveness. The advanced prediction models like RNN, GRU, and LSTM are applied to the prepared athlete data after the collection and preprocessing of data.

This step is necessary to find out the best and most interpretable model among all for marathon performance forecasting. Deep learning model selection component executes the model selection process by rigourously testing different deep learning techniques based on their ability to predict race times. This assessment is done in the module DL models; hence, the model with the greatest predictive accuracy is selected for further analysis. This module of DL model evaluation and selection will make sure that the selected model is reliable and accurate.

Another key aspect of the framework is the analysis of the predictions of the chosen model. This prediction analysis gives insight into the expected performance of the athlete and provides a good basis for making relevant decisions toward improvement in the future. The process of model selection is detailed in the next subsection.

B) DL Selection Evaluation

Here in this section, the evaluation strategy for deep learning model selection algorithm performance is considered for the estimation of marathon finish time. Here, different deep learning models will be trained on the data set and cross-checked with test data to make the prediction values obtained reliable. Different models explored in the current study based on deep learning incorporate RNN, LSTM, and GRU. From these, automatically, the selection of the most suitable deep learning model will be made. The selected models are designed to handle time-series data, which is the performance of the athletes during training. The selected models will be used to forecast the finishing times for the future. Then, the algorithm will evaluate the various predictions using some important performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics give a perfect insight into the accuracy of the model. The formula for these metrics is as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} \left(y_{pt} - y_t\right)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_{t=1}^{n} |y_{pt} - y_t|}{n} \quad (2)$$

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left|\frac{y_{pt} - y_t}{y_t}\right| \quad (3)$$

Here, y_{pt} shows the predicted values and y_t is the actual value and while n is total number of entries in the data set, Here MAPE for RNN, LSTM and GRU are calculated which is to be used to find the best Deep learning model, for marathon race time. Finally, selected Deep learning model has tested against the best times to complete race. This is summarized in the evaluation process outlined in Algorithm 1. It accepts the athletes' workout data and the potential deep learning models as inputs, producing predictions for race completion times as the output. In such a way, the algorithm compares different models using MAPE for their predictions and chooses the model that reaches the highest accuracy.

3 Experiments and evaluation

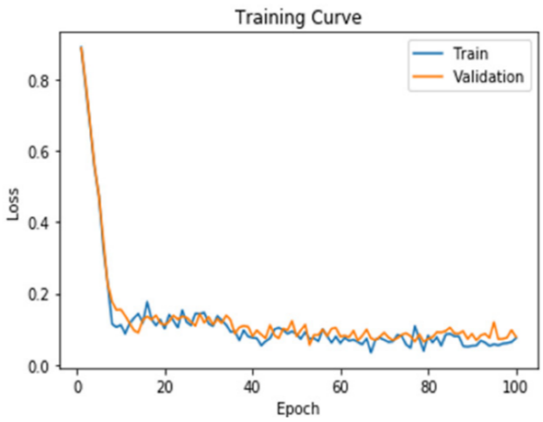
This section outlines the experimental evaluation conducted to evaluate the effectiveness of our prediction models. It begins with an overview of the experimental setup, followed by details on the dataset collection process, and then explains the procedures for data preparation and preprocessing. Lastly, the results are discussed along with a thorough analysis. The features of the data are shown in Table 2.

A) Experimentation Setup

To implement the three Deep Learning models, we selected PyTorch, an open-source, comprehensive framework for machine learning [5][14]. Additionally, we utilized Jupyter Notebook, an open-source web-based application that enables users to develop documents integrating executable code, mathematical equations, graphical representations, and descriptive text. Besides, as a baseline for comparisons, we consider a standard linear regression machine learning model.

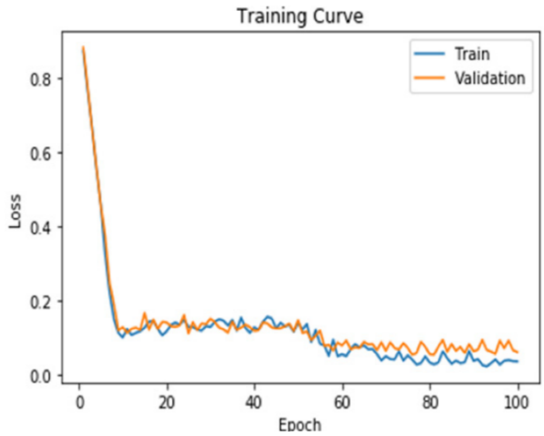
B) Dataset

Data on running a marathon were chosen for the experimental verification of the proposed model. Running is very often described as one of the most available sports for a person of average physical condition because it perfectly fits into a hectic schedule and can be performed virtually anywhere and anytime Thus, running as a kind of sport has become very popular all over the world. The



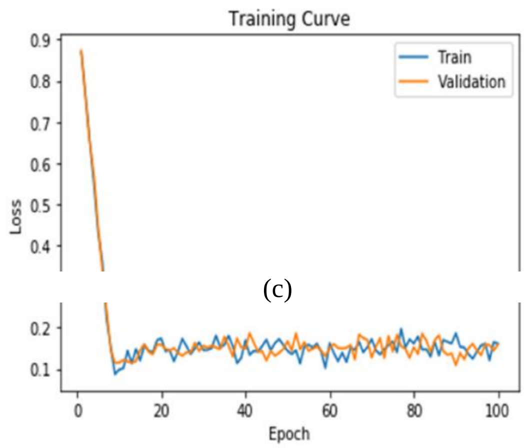
(a)

dataset used in this work is on training sessions from professional athletes who were set to participate during the 2017 Boston Marathon, observed over their five-month



(b)

preparation phase [21]. Known for its prestige and global recognition, the Boston Marathon stands as one of the most celebrated and widely attended marathons in the world.; every year, it gathers thousands of participants. Thus, any dataset from this marathon is quite sizeable,



(c)

Figure 3: Training curves of prediction error (MAPE) for RNN, GRU, and LSTM models with 50 hidden states. The subplots show RNN stabilizing at 0.10 MAPE, GRU experiencing overfitting after epoch 55, and LSTM stabilizing around 0.15 MAPE.

adding to the reliability and accuracy of our results. Each of the records collected contains an array of features such as the name of the athlete, session date, running length in meters, duration of run, pace in minutes per kilometer, average pace of workout, and elevation, which means the sum of all gains in elevation throughout the course of the activity. The data is from 549 athletes of the April 2017 Boston Marathon and 23,763 training activities these athletes have done in five months prior to the marathon. Figure 2 presents the distribution of activities data and race paces. From this, the distribution of distance, pace, and elevation can be identified following lognormal, Gaussian, and exponential patterns, respectively. Moreover, the marathon race pace exhibits a normal distribution with a mild rightward skew.

C) Data Preparation and Pre-Processing

The data used in this work had to be prepared and preprocessed before feeding the machine learning models. To this end, we employed the Talend Data Preparation tool [20] to import files with information on athletes via its user-friendly interface. It provides several functionalities: parsing of files, giving recommendations on data cleansing, among others. Besides, it gives the capability of plotting charts and metrics that allow visual data quality assessment. We also used Trifacta Wrangler (version 3.0.1-client1+push2) for the preparation, preprocessing, and assessment of data quality metrics [22]. In addition to the mentioned tools, during the whole process of data cleaning, different Python libraries (datetime, pandas) were used. Among them are the datetime library for time format data processing and pandas for cleaning and normalization. These tools and libraries put together allowed for fast and qualitative preparation of the data.

D) Results and Discussion

This section is devoted to performance testing of the proposed model, where each algorithm of prediction accuracy is tested, so the best method is selected within the model.

We run RNNs, LSTMs, and GRUs models by considering 25 and 50 hidden states. We compare these two results, which have almost the same graph; the 50 hidden state configured model demonstrates a slight difference in terms of accuracy. We further optimized this and present results when the deep learning models were trained on a pre-processed data set cleaned by the three-sigma rule of statistical quality control [9]. In this, only values within ± 3σ from the mean were kept. We were able to retain 93.3% of the dataset from this cleaning. This cleaning had a positive effect on the models' performance reflected by the MAPE values listed for each model in Table II. Thus, according to the performance based on MAPE values and considering other benchmark models in this dataset, GRU with 50 hidden states had selected the model selection process as the best-performing algorithm.

This made the selection module finally select the most optimal model to estimate finishing time: GRU.

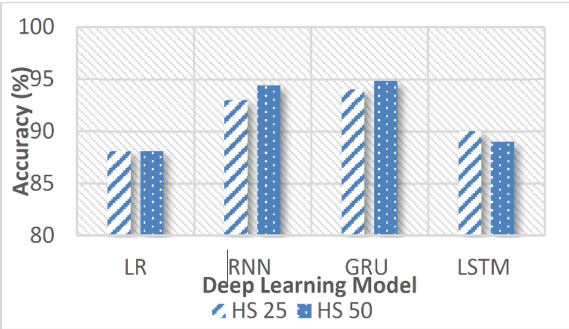


Figure 4: Accuracy comparison of deep learning models, showing GRU (95%) outperforming RNN (94%) and LSTM (89%) after outlier removal. All models exceed the baseline linear regression.

The training plots in Figure 3 give an idea of the learning behavior of the deep learning models being investigated. The RNN model (Figure 3a) exhibits a steep decline in MAPE during the initial epochs, indicating its ability to learn short-term dependencies. It, however, plateaus very quickly, at around epoch 15, which means that it gets stuck in a local optimum. This restriction is in line with the recognized difficulty of vanishing gradients for RNNs, making it difficult for them to efficiently learn long-term dependencies. The GRU model (Figure 3b), however, demonstrates a more definite and prolonged decrease in error and continues to perform well through epoch 50. Its design, incorporating reset and update gates, enables it to manage sequential dependencies more effectively than the RNN. Interestingly, beyond epoch 55, the GRU model starts overfitting, with the training loss still decreasing but the validation loss plateauing, showing the typical overfitting behavior for powerful deep learning models when the data is moderately sized. The LSTM model (Figure 3c) takes longer to converge and plateaus at a higher MAPE of around 0.15. Although LSTM is built to allow longer-term dependencies than RNN, its more complicated architecture might not be fully utilized in this study given the moderate-sized dataset and can lead to slower learning and worse performance compared to that of GRUAdditionally, deep learning models have been tested based on performance concerning the MAPE metric. From Figure 4, after removing the outliers, the highest accuracy stands at 95%, obtained by the GRU model with 50 hidden states compared to 94% and 89% obtained by RNN and LSTM models respectively. Besides this, all these deep learning models outperform the baseline LR model by a high margin, thus again proving how effective deep learning models are when applied for the task of predicting marathon finish times.

The results in Table 2 and Figure 4 reinforce the superiority of the GRU model, which achieved the lowest MAPE (5.2 percent) and the highest accuracy (95 percent) after outlier removal, compared to the RNN (5.6 percent MAPE, 94 percent accuracy) and LSTM (6.5 percent MAPE, 89 percent accuracy). The improved performance of GRU can be attributed to its efficient gating mechanism, which allows it to maintain crucial information over longer sequences while avoiding unnecessary complexity. Unlike the RNN, which lacks gates and is prone to issues such as vanishing gradients, the GRU's gates enable it to control the flow of information effectively. Compared to LSTM, which has an even more complex three-gate structure, GRU achieves a balance of simplicity and expressiveness, making it less prone to overfitting and faster to train. This architectural efficiency is particularly beneficial when working with datasets of moderate size, such as the one used in this study, where GRU's design allows it to capture both short- and long-term dependencies with minimal computational overhead.

Table 2*:* Comparison of MAPE values for different models (Linear Regression, RNN, GRU, and LSTM) with 25 and 50 hidden states, evaluated on datasets with and without outliers.

Performance Metric	Linear Regression (LR)	RNN	GRU	LSTM
Dataset Without Outliers - 25 Hidden States	0.10	0.07	0.06	0.10
Dataset Without Outliers - 50 Hidden States	0.10	0.056	0.052	0.11
Full Dataset - 25 Hidden States	0.11	0.11	0.089	0.122
Full Dataset - 50 Hidden States	0.11	0.12	0.10	0.104

The baseline linear regression model, however, performed a much worse MAPE of approximately 10 percent, indicating its built-in deficiency in this regard. Linear regression has the assumption of static linear dependency between input features and output, failing to recognize the dynamic, sequential nature of training data. Marathon performance is not only a function of stand-alone variables such as pace or distance but also of the collective impact of training over time, where adaptation, recovery, and fatigue interact with each other in intricate ways. The linear regression model does not have the ability to identify and take advantage of these temporal patterns, which is why its relatively poorer predictive power. It is this realization that highlights the overriding importance of using sequence-based deep learning models like GRU, which are specifically designed to deal with the temporal aspect of workout information and provide more accurate predictions of athletic performance.

4 Conclusion

Enhancing the performance of the athletes to higher levels, both nationally and internationally, promotes societal cohesion in society and retains an identity in global status. This may be done through an analysis of current performances, investigating work-out habits, and then projecting forward to higher performances in sports competitions. A holistic process of modeling and analyses would give detailed specific training required that leads to the standard of the performance being maximized.

This paper describes deep learning models in forecasting athlete performance in competitive eventsand tournaments. On the other hand, the accuracy of a prediction can works as a good motivator toward continuing and increasing training to meet target times and increase the likelihood of achieving success. In addition, it allows showing it to the athletes, which may influence their approach in training, thus enabling them to work out their weaknesses and improve the general performance. Moreover, this model will create great value in monitoring the progress of athletes and giving them exact training to help them in their preparation process and incremental improvement in competitive performance. This research makes two major contributions: investigating various Deep Learning models to find the best among them for the prediction of performance of an athlete, and proposing a Deep Learning model selection algorithm that will ensure the accuracy of the performance prediction for competitions. The proposed framework allows the evaluation of a number of Deep Learning models, showing that these models outperform traditional methods in predicting race times. Among these, the GRU model showed the highest accuracy, outperforming RNN, LSTM, and standard linear regression models.

One limitation of this study is the small size of the training dataset; although encouraging results are achieved, they limit applicability to larger scales. A future study could be presented with enhanced studies using larger datasets of actual data on finishers' running patterns from famous marathons in Tokyo, London, and Berlin. Furthermore, customized training schedules, novelty in injury prevention approaches, and a detailed recovery strategy may provide further extensions to the framework. Advanced ensemble methods include fine-tuning Random Forest with Deep Learning to greatly improve prediction accuracy and thus better results, which could be a subject of further research.

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