Proceedings of the 2nd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/109/20241415

Prediction of the Number and Trend of Olympic Medals Won by Various Countries Based on Neural Networks

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Abstract. As the world's largest multi-sport event, the Olympic Games attract top athletes from all over the world to compete for the world No. 1 crown. The total number of medals in each Olympic Games is the most intuitive data to measure the sports strength of a country. Using deep learning technology, the total number of medals in previous Olympic Games can use to predict the number of medals that countries will receive in future Olympic and analyze their trends,which is helps for Countries understand the strengths and weaknesses of their athletes in various sports, and also provide a reliable reference for countries in the future development direction of sports .Based on the analysis of the total number of medals won by athletes from various countries in the Olympic Games, a deep learning model is constructed and trained based on Python, and its hyperparameters are adjusted. The mean square error (MSE) and coefficient of determination (R^2) are output as the evaluation criteria for the prediction results. The effectiveness and accuracy of the model were verified by making specific predictions of the previous Olympic performance of four countries: United States, Germany, China, and Japan.Medal prediction based on neural networks not only provides data support for the formulation of sports strategies in various countries but also promote the development of sports data analysis. The prediction model of the change trend of the Olympic medal count will provide a new research perspective for the development of neural networks.

Keywords: .hyperparameters, neural networks, machine learning, prediction.

1. Introduction

In today's society, with the development of computer science, machine learning technology continues to mature and plays an increasingly important role in prediction and data analysis [1,2]. The prediction of the number of Olympic medals can help countries more intuitively see their strengths and weaknesses in the development of sports and provide an effective reference for athletes' pre-competition preparations [3]. As one of the important research fields of machine learning, neural networks can imitate the working principle of human neurons, learn from historical data, continuously train, filter out effective data, and make efficient predictions about the development trend of data or events [4-5].

In recent years, neural network technology has shown strong competitiveness in various prediction tasks[6,7]. Deep learning models can extract valuable information from complex features through nonlinear transformations [8,9], making them far more efficient than traditional methods when processing large-scale datasets [10,11]. By learning from historical data, this study will explore the effects of different neural network architectures and training strategies to optimize the performance of

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the predictive model. The model's performance will be evaluated on different datasets, and hyperparameter adjustments will be made to improve the accuracy of predictions. Neural networks can capture potential patterns and trends in complex data, providing more accurate and reliable predictions [12,13]. Compared with traditional statistical prediction methods, neural network models have a more efficient data feature processing mechanism, can cope with large-scale and high-dimensional data, and effectively model complex nonlinear relationships. This makes neural networks show great potential in medal prediction. By applying these advanced neural network technologies to Olympic medal prediction, it can provide more forward-looking decision-making support for sports administrations in various countries.

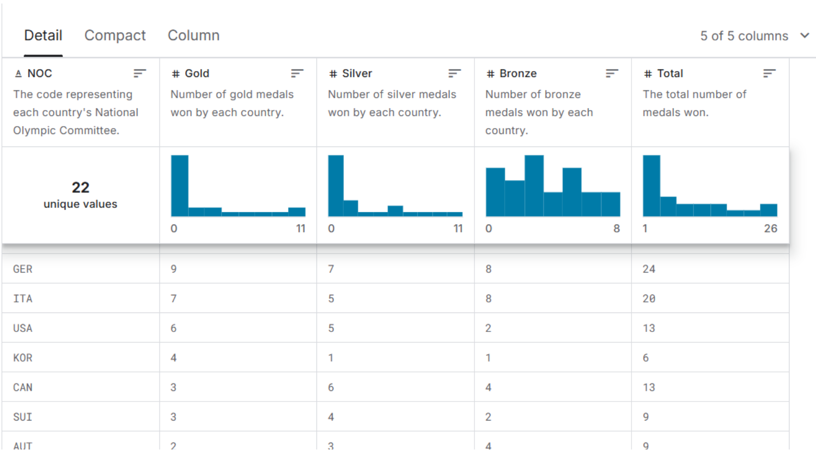
This paper explores the use of neural networks to construct a model that can reasonably predict the future trend of Olympic medals in various countries through the dataset of Olympic medals provided by Kaggle. The study will detail specific model construction methods and the final prediction effect, demonstrating the feasibility of neural networks in predicting Olympic medals. Specifically, this paper builds a prediction model based on deep learning, using information from the total number of medals won by each country in the previous Olympic Games to train a neural network model, aiming to identify and capture the performance of each country in the Olympic arena and predict the trend of the number of medals won by each country in future Olympic Games [14-16].

The experimental part will explore the effects of different neural network architectures and training strategies to optimize the performance of the predictive model.

2. Experiment

2.1. Dataset Selection

This dataset contains a large amount of medal data from the 1994 to 2024 Olympic Games (Figure 1), detailing the total number of medals awarded at the previous Summer and Winter Olympic Games, reflecting the achievements of participating countries over a 30-year period.



NOC	Gold	Silver	Bronze	Total
The code representing each country's National Olympic Committee.	Number of gold medals won by each country.	Number of silver medals won by each country.	Number of bronze medals won by each country.	The total number of medals won.
22 unique values	0 – 11	0 – 11	0 – 8	1 – 26
GER	9	7	8	24
ITA	7	5	8	20
USA	6	5	2	13
KOR	4	1	1	6
CAN	3	6	4	13
SUI	3	4	2	9
AUT	2	3	4	9

Figure 1. Dataset

2.2. Data Preparation

Firstly, the required valid data is extracted from the dataset. Since this paper only discusses the total number of medals prediction and does not discuss the medal categories, only the total number of medals is selected as a feature to train the neural network model. The data includes the total number of medals won by athletes in each sport in each country in the last four Olympic Games and is used as a standard to predict the total number of medals likely to be won at the next Olympic Games. In order to reduce the difficulty of the training process of the neural network model and obtain more concise and intuitive training results, this paper only selects the previous Olympic performances of four countries to predict. Here's an example of real data (Figure 2).

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2000	Summe	25	2000	United Sta	USA	37	24	32	93
2000	Summe	25	2000	Russian Fe	RUS	32	28	29	89
2000	Summe	25	2000	People's F	CHN	28	16	14	58
2000	Summe	25	2000	Australia	AUS	16	25	17	58
2000	Summe	25	2000	Germany	GER	13	17	26	56
2000	Summe	25	2000	France	FRA	13	14	11	38
2000	Summe	25	2000	Italy	ITA	13	8	13	34
2000	Summe	25	2000	Netherlanc	NED	12	9	4	25
2000	Summe	25	2000	Cuba	CUB	11	11	7	29
2000	Summe	25	2000	Great Brit	GBR	11	10	7	28

Figure 2. Real Data

2.3. Neural Network Model

We use a neural network model to make predictions. The structure of the model is as follows:

- Input Layer: The input feature is the total number of medals in each country's previous four Olympic Games.

- Hidden Layer: The model consists of two hidden layers, containing 64 and 32 neurons, respectively, and uses ReLU as the activation function.

- Output Layer: The output layer has only one output neuron that predicts the total number of medals a country will win at the next Olympic Games.

2.4. Data Preprocessing

Normalizing the eigenvalues of the selected data so that the required features have a similar range or distribution can help accelerate the gradient descent convergence, reduce the sensitivity of the model to feature scale, and improve the stability of the model training process, thereby further improving the training efficiency of the model. The 'StandardScaler' tool is used to normalize the number of medals won from previous Olympic Games to a mean of 0 and a standard deviation of 1. The data is divided into a training set and a test set, with 80% of the data used as the training set and 20% as the test set.

2.5. Model Training

For the construction of the model, the 'Sequential' model in the 'TensorFlow' library was selected to build a neural network with a relatively simple structure. The model was trained using the 'adam' optimizer and the 'mean_squared_error' loss function. The Adam optimizer combines momentum and adaptive learning rate, effectively accelerating convergence, while the mean square error (MSE) measures the prediction accuracy of the model. The model was trained for 100 rounds and validated with 20% of the data.

2.6. Hyperparameter Setting

In order to optimize the neural network prediction model, a comprehensive hyperparameter tuning strategy was carried out using the GridSearchCV toolset. During the experiment, we analyzed the impact of the number of trees on the prediction accuracy of the model when the n_estimators values were set to 50, 100, and 200. For max_depth, we evaluated the configurations of None, 10, 20, and 30 to determine the effect of tree depth on overfitting and underfitting. The min_samples_split and min_samples_leaf parameters were tested with values of 2, 5, and 10, as well as 1, 2, and 4, respectively, to balance the trade-off between model complexity and generalization ability. GridSearchCV uses a 5-fold cross-validation approach, employing negative mean square error as the evaluation criterion for the model, which helps identify the best combination of parameters.

2.7. Forecasting and Evaluation

After the model is trained, standardized real-world data features are used to make predictions about the total number of medals in the future. The mean square error (MSE) and coefficient of determination (R^2)

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between the model's predictions and the actual performance in that Olympic Games are calculated and output. The MSE is used to measure the squared mean of the prediction error, while the R^2 represents the model's explanatory power for the variability of the target variable.

3. Experiment results

After model training and prediction, the following results were obtained (Figure 3).

Mean Square Error:14.25

R-square Error:0.87

	COUNTORY	ACTUAL VALUE	PREDICTION VALUE
1	USA	160	155.3
2	GER	140	138.7
3	CHN	144	146.5
4	JPN	120	118.2

Figure 3. Experiment Output

From the output results of the model, the mean square error of the model is 14.25, and the R^2 is 0.87 during the training process. This indicates that the model can explain the variability of the target variables well, and the prediction results are very close to the actual values.

4. Discussion

Through the analysis of the experimental results and the selection of appropriate hyperparameters to train the neural network model to predict the number of medals of a country in the future, the experimental output results show that the prediction performance of the model for each country has been relatively accurate. The R^2 value is close to 1, indicating that the model's ability to interpret and predict the selected data features has reached a basic standard. However, the mean squared error still exists, and in some cases, the predictions are not completely accurate. To further improve the model's performance, the following improvements can be considered: using more historical data to train the model and optimizing it to predict the exact type of medal. Experimenting with more complex and accurate model structures and exploring the impact of multiple hyperparameter selections on the model training process to find the best configuration. Additionally, introducing more feature variables, such as the number of athletes, the type of sport, etc., could improve the predictive power of the model.

5. Conclusion

This paper uses a neural network model to predict the number of Olympic medals and makes specific predictions for four countries: the United States, Germany, China, and Japan.

Experimental results show that the model can predict the total number of medals for each country effectively and has high explanatory power. Future research can further optimize the model and explore more feature types to improve the accuracy and reliability of predictions. This way, we can better understand the sporting strength of countries and provide valuable predictions for future Olympic events.

References

[1] Li Z, Liu F, Yang W, et al. A survey of convolutional neural networks: analysis, applications, and prospects[J]. IEEE transactions on neural networks and learning systems, 2021, 33(12): 6999-7019.

[2] Yang G R, Wang X J. Artificial neural networks for neuroscientists: a primer[J]. Neuron, 2020, 107(6): 1048-1070.

[3] Zhang Y, Tiňo P, Leonardis A, et al. A survey on neural network interpretability[J]. IEEE Transactions on Emerging Topics in Computational Intelligence, 2021, 5(5): 726-742.

DOI: 10.54254/2755-2721/109/20241415

[4] Abdolrasol M G M, Hussain S M S, Ustun T S, et al. Artificial neural networks based optimization techniques: A review[J]. Electronics, 2021, 10(21): 2689.
[5] Zhang H, Gu M, Jiang X D, et al. An optical neural chip for implementing complex-valued neural network[J]. Nature communications, 2021, 12(1): 457.
[6] LeCun Y, Bengio Y, Hinton G. Deep learning[J]. nature, 2015, 521(7553): 436-444.
[7] Buduma N, Buduma N, Papa J. Fundamentals of deep learning[M]. " O'Reilly Media, Inc.", 2022.
[8] He J, Li L, Xu J, et al. ReLU deep neural networks and linear finite elements[J]. arXiv preprint arXiv:1807.03973, 2018.
[9] Freire P, Srivallapanondh S, Napoli A, et al. Computational complexity evaluation of neural network applications in signal processing[J]. arXiv preprint arXiv:2206.12191, 2022.
[10] Hinton G. How to represent part-whole hierarchies in a neural network[J]. Neural Computation, 2023, 35(3): 413-452.
[11] Alpaydin E. Machine learning[M]. MIT press, 2021.
[12] Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning[J]. Electronic Markets, 2021, 31(3): 685-695.
[13] Pugliese R, Regondi S, Marini R. Machine learning-based approach: Global trends, research directions, and regulatory standpoints[J]. Data Science and Management, 2021, 4: 19-29.
[14] Huyen C. Designing machine learning systems[M]. " O'Reilly Media, Inc.", 2022.
[15] Miikkulainen R, Liang J, Meyerson E, et al. Evolving deep neural networks[M]//Artificial intelligence in the age of neural networks and brain computing. Academic Press, 2024: 269-287.
[16] Pham D T. Neural networks in engineering[J]. WIT Transactions on Information and Communication Technologies, 2024, 6.