BEDEN EĞİTİMİ SPOR SAĞLIK VE EFOR DERGİSİ

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# FORECASTING THE NUMBER OF PHYSICAL EDUCATION TEACHERS TO GRADUATE IN TÜRKIYE BY 2030 UTILIZING ARTIFICIAL NEURAL NETWORKS AND TIME SERIES ANALYSIS

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## ABSTRACT

Türkiye possesses a rather substantial youth population, rendering sports infrastructure essential. Physical education instructors are critical in advocating for fitness, imparting knowledge of physical activities, and identifying athletic potential in school-aged children and adolescents who allocate a significant amount of time to activities outside of school hours. The evolution of technology has integrated artificial intelligence into our daily lives, with one of its advantages being the ability to forecast future results. This study seeks to quantify the anticipated number of physical education instructors graduating from 2023 to 2030 via diverse methodologies. The 0, 0, 1 model predicts a 1.66-fold increase in the number of physical education instructors graduating in 2030 compared to 2022. The Bayesian regularization technique forecasts a 1.20-fold increase. The projected range for the number of physical education instructors graduating in 2030 is between 5030 and 6979.

**Keywords:** Machine learning, sensitivity analysis, forecasting, physical education

# YAPAY SINIR AĞLARI VE ZAMAN SERISI ANALIZI KULLANILARAK 2030 YILINA KADAR TÜRKIYE'DE MEZUN OLACAK BEDEN EĞITIMI ÖĞRETMENI SAYISININ TAHMINI

## ÖZET

Türkiye, oldukça büyük bir genç nüfusa sahip olduğundan, spor altyapısı hayati önem taşımaktadır. Beden eğitimi öğretmenleri, okul çağındaki çocuklar ve ergenler arasında fiziksel aktiviteler hakkında bilgi vermek, spor potansiyelini belirlemek ve okul saatleri dışında önemli miktarda zaman harcayan bireyler arasında fitnessi teşvik etme konusunda kritik bir rol oynamaktadır. Teknolojinin evrimi, yapay zekayı günlük yaşamımıza entegre etti ve bunun avantajlarından biri gelecekteki sonuçları tahmin etme yeteneğidir. Bu çalışma, 2023'ten 2030'a kadar mezun olacak beden eğitimi öğretmenlerinin beklenen sayısını çeşitli yöntemlerle nicelleştirmeyi amaçlamaktadır. 0, 0, 1 modeli, 2022'ye kıyasla 2030'da mezun olacak beden eğitimi öğretmenlerinin sayısında 1,66 kat artış öngörmektedir. Bayesyen düzenleme tekniği, 1,20 kat artış öngörüyor. 2030 yılında mezun olacak beden eğitimi öğretmenlerinin sayısı için öngörülen aralık 5030 ile 6979 arasındadır.

**Anahtar Kelimeler:** Makine öğrenimi, hassasiyet analizi, tahmin, beden eğitimi

## 1. INTRODUCTION

Teachers are critical to the future of their societies and education systems. They are undoubtedly the most indispensable element (Çelen & Bulut, 2019). As the field of exercise and sport sciences continues to grow and develop, there will be those who choose to study and pursue a career in exercise and sport sciences (Spittle et al., 2021). It is worth noting that there has been a significant increase in the number of graduates with a degree in exercise and sport sciences over the last two decades (Stevens et al., 2018). Excessive exposure to technological materials such as television and computers in children can cause various body posture disorders, physical inactivity, weight gain, decreased muscle strength, and changes in bone tissues (Özyürek et al., 2015).

One of the main aims of physical education is to enhance the physical, mental, social, and emotional development of children (Gülüm & Bilir, 2011). To promote lifelong physical health, it is important for schools to build a strong foundation in physical activity. One way to achieve this is to emphasize to young people the importance of participating in physical activity throughout their lives, and this will be with the help of physical education teachers (Hein et al., 2012). Physical education classes are one of the least emphasized subjects in schools. The main reasons for this are a lack of sports fields, a lack of interest among teachers and parents in sports and physical activities, and a lack of physical education teachers. A major deficiency in the education system is the lack of emphasis and processing of physical education lessons (Özer & Özer, 1998)

Artificial neural networks (ANN), which are based on the way the human brain learns and changes, are computer systems that are programmed to learn and create new information on their own. They are used as a tool for predictive methods (Şenol et al., 2021). The autoregressive integrated moving average (ARIMA) model is a prevalent framework for forecasting future values of a time series based on historical data (Sun, 2021). The choice of a suitable exponential smoothing approach should align with the components of the time series, and the Holt-Winters method yields effective predictions for such series (Bas et al., 2021).

The literature analysis reveals a scarcity of research on forecasting in the realm of sports in Türkiye, and to the authors' knowledge, there are no studies specifically addressing physical education instructors. Atasoy et al. (2017) used an ANN to model the quantity of licensed combat sports athletes in Türkiye from 2007 to 2016 and forecasted the number of licensed

athletes for 2017 and 2018. Dalkılıç et al. (2017b) used an ANN to forecast the number of licensed wrestlers in Türkiye for 2017 and 2018, utilizing data from 2007 to 2016. Dalkılıç et al. (2017a) utilized ANN to forecast the number of certified athletes with impairments for the years 2017 and 2018, employing data from 2006 to 2017. Komar et al. (2023) utilized ANN modeling to forecast the outcomes of men's and women's volleyball super league matches in Türkiye from 2013 to 2020. Çolak and Şenol (2023) utilized ANN to forecast the number of licensed athletes in Türkiye from 2019 to 2030, modeling the data from 2004 to 2018 for this analysis.

The findings of this study will significantly influence the assessment of the demand for physical education instructors in Türkiye and the formulation of requisite policies to address this need. The acquired estimations will inform the feasibility studies generated by the Ministry of National Education and will underpin choices about teacher recruitment and the capacity planning of teacher training programs based on empirical facts. Moreover, cultivating an adequate quantity of proficient physical education instructors would enhance the proliferation of sports culture in educational institutions, elevate student physical activity levels, and therefore bolster our nation's achievements in sports and education.

## 2. Theoretical Method

### 2.1. Artificial neural network

ANNs are computational models derived from biological neural networks in the human brain, capable of learning from data to identify patterns and provide predictions (Zhu & Liu, 2022). To construct an ANN, one must pick a collection of input variables and ascertain the best suitable network architecture through experimentation (Fanoodi et al., 2019). The ANN evaluates the output reaction of the subject under investigation in relation to the input action, and then performs data processing and mathematical computations to determine the mathematical relationship between the object (He et al., 2023). A neural network is characterized as a highly parallel processor composed of elementary units referred to as neurons (Şenol, 2025). The network comprises a number of single-layer neuron chains and weights facilitating their connection (Singh et al., 2017). Rather than storing information in designated areas as in conventional computer memory, ANNs distribute data around the network, utilizing weighted values based on the interconnections among neurons. Instead of explicitly

constructing them for a specific purpose, artificial neural networks acquire knowledge through training on existing data. Network learning entails modifying the weights to achieve the intended purpose (Şenol et al., 2021). The ANN derives its data by comparing it with the output value, which then leads to corresponding adjustments in the weights (Elibol, 2025). Training persists until the error value, defined as the discrepancy between the input value and the target value, falls below a specified threshold. All weights stabilize and the training process concludes when the error value falls below the acceptable threshold (Kalogirou, 2001). The backpropagation process's convergence is slow, occasionally leading to overfitting or memorization. Algorithm can employ algorithms like Levenberg-Marquardt backpropagation (LM) and Bayesian regularization backpropagation (BR) to address these issues (Teke et al., 2023). algorithm is an effective technique for addressing nonlinear regression problems using nonlinear least squares. The BR technique improves generalization capacity by modifying the training parameters of the ANN, and it also minimizes generalization error (You & Lu, 2023). The research includes four factors in the input layer. The input parameters include population, student count, education preparation allowance, and the Ministry of National Education (MNE) budget. The optimal amount yielding the maximum efficiency results. The output layer represents the quantity of graduated physical education teachers (GPET). The developed ANN model has 4 input parameters, 8 hidden neurons, and 1 output parameter (Figure 1). LM and BR techniques were used for the artificial ANN and as a result of experimental trials, it was determined that 8 hidden neurons gave the best performance. The input data is represented by the input layer $X_i$. Wh is the vector of input weights that connects the inputs. The output weight vector, $B_h$, links each result. $N_i$ in the output layer comprises the output information (Al-Kouz et al., 2019).

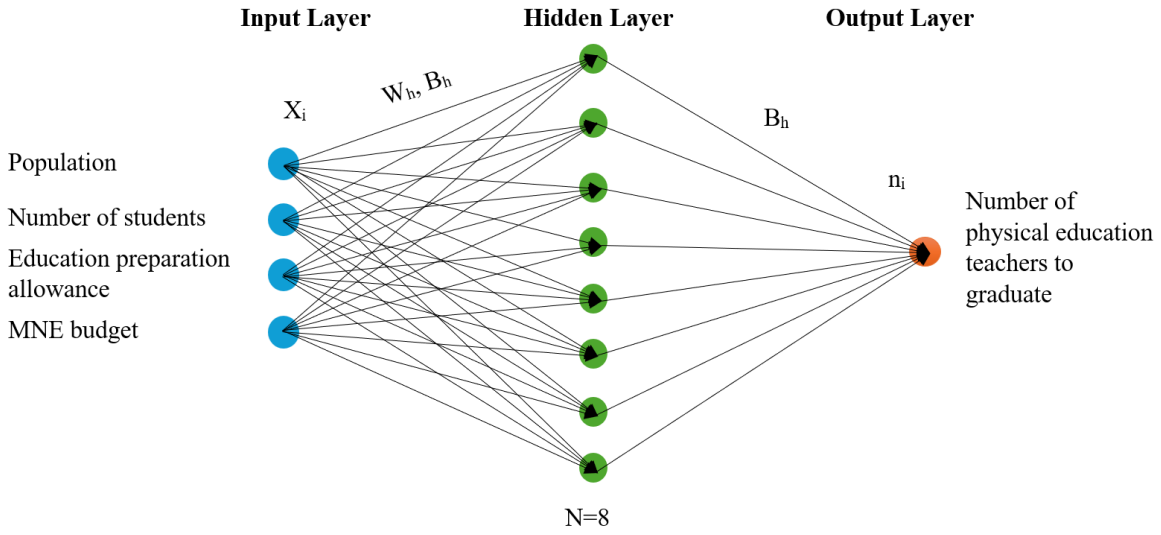


**Figure 1.** Artificial Neural Network architecture (MNE: Ministry of National Education).

### 2.1.1 Sensitivity analysis

Garson's algorithm and Yoon's algorithm were utilized as sensitivity studies in ANN models constructed with the LM and BR. The calibrated link weights of the trained ANN model demonstrate the influence of the input factors on the output variable. Thus, establishing a weight distribution between the input and output layers allows for the identification of major and secondary correlations between the input variables and the output variables. Equation 1 presents the formula for the Garson algorithm. In this equation, $R_{ij}$ denotes the relative significance (RI) of the input variables, whilst wij and wjk signify the connection weights between the input layer and the hidden neuron layer and between the hidden neuron layer and the output layer, respectively (Zhao et al., 2023).

$$G\ddot{O}garson(\%)_{ik} = \frac{\sum_{j=1}^{m}((|W_{ij}|/\ \sum_{i=1}^{n}|W_{ij}|)x|W_{jk}|)}{\sum_{i=1}^{n}\{\sum_{j=1}^{m}((|W_{ij}|/\ \sum_{i=1}^{n}|W_{ij}|)x\ |W_{jk}|)\}} \quad (1)$$

Equation 2 expresses Yoon's algorithm as the ratio of the input parameter to all other parameters. Wij and Wjk, respectively, indicate the connection weights from the input layer to the hidden neuron layer and from the hidden neuron layer to the output layer, while Vik represents the connection weight of the output layer (da Costa et al., 2021).

$$RIyoon(\%)_{ik} = \frac{\sum_{j=1}^{h} W_{ij} v_{jk}}{\sum_{i=1}^{m} | \sum_{i=1}^{h=1} W_{ij} v_{jk} |} \text{ x100} \quad (2)$$

## 2.2. Autoregressive integrated moving average model (ARIMA)

The autoregressive integrated moving average (ARIMA) model is a dependable approach for time series research (Şenol et al., 2024a). The autoregressive order (p), the differencing order (d), and the moving average order (q) need to be calibrated before the ARIMA model can be used to study time series (Zhang & Zhou, 2024). The ARIMA model, or Box-Jenkins approach, is employed to develop a time series model using univariate time series data (Çolak & Çolak, 2024). The model comprises three components: the autoregressive (AR) component, the integrated (I) component, and the moving average (MA) component (Şenol et al., 2024b). The AR term refers to the correlation between past and present observations, and the MA term to the structure of the residuals (errors) and the fact that most univariate time series data tend to show non-stationary trends that go up and down (Ray et al., 2021). The ARIMA (p, d, q) model is a specific case of the ARMA (p, q) model, in which the differencing parameter d equals zero (Ray et al., 2023). This study favors the ARIMA models [0, 1, 0], [0, 1, 1], [1, 1, 1], and [1, 1, 0]. Equation 3 displays the ARIMA general formula.

$$Y_t = C + \Phi_1 * Y_{t-1} + \ldots + \Phi_p * Y_{t-p} + \theta_1 * e_{t-1} + \ldots + \theta_q * e_{t-q} \quad (3)$$

## 2.3. Holt-Winters method

The Holt-Winters (HW), an exponential smoothing technique, analyzes time series data by breaking it down into trend, seasonal, and error components. The exponential smoothing function methodology reduces irregularities in time series data to improve clarity and has the capability to forecast future values, making it an optimal method for achieving precise readings (Gelper et al., 2010). Equation 4 displays the HW method's formula for forecasting future observations. Lt denotes the data level, Tt denotes the trend, St denotes the seasonal component, and Ft + k indicates the projection for the subsequent k periods (Rashidi et al., 2022).

$$F_{t+k} = (L_t + kT_t)\, St_{-m+k} \quad (4)$$

## 2.4. Model performance metrics

The performance metrics of the models developed using LM, BR, ARIMA, and HW methods are computed using the formulas for mean square error (MSE), root mean square error (RMSE), sum of squares error (SSE), mean absolute percentage error (MAPE), and correlation coefficient ($R^2$), as detailed in Table 1.

**Table 1.** Model performance metrics formula table.

| Performance metrics | Formula |
|---|---|
| MSE | $\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}$ |
| RMSE | $\sqrt{\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{n}}$ |
| SSE | $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ |
| MAPE | $\frac{100}{n}\sum i = 1 \frac{\lvert yi - \hat{y}i \rvert}{yi}$ |
| $R^2$ | $1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ |

The Turkish Statistical Institute (TurkStat) (TurkStat, 2024), MNE (RTMNE, 2024), and DrDataStats (DrDataStats, 2024) provided the input and target characteristics used to determine Türkiye's GPET for 2023-2030. The input parameters include population, student count, educational preparation allowance for instructors, and MNE budget. The quantity of certified physical education instructors is the goal criterion. Data for these factors is available from 2014 to 2022. The population parameter is measured in millions ($10^6$), the number of students parameter is also in millions ($10^6$), and the MNE budget is quantified in hundreds of millions of Turkish liras ($10^9$); however, the parameters for educational preparation allowance and GPET are unitless.

**Table 2**. Data of input parameters by years.

| Years | Population ($10^6$) | Number of Students ($10^6$) | Education Preparation Allowance (TRY) | Ministry of National Education Budget (TRY) ($10^9$) |
|---|---|---|---|---|
| 2014 | 77.7 | 17.6 | 850 | 55.7 |
| 2015 | 78.7 | 17.6 | 950 | 62.0 |
| 2016 | 79.8 | 17.7 | 1000 | 76.4 |
| 2017 | 80.8 | 17.9 | 1050 | 85.0 |
| 2018 | 82.0 | 18.1 | 1130 | 92.5 |
| 2019 | 83.2 | 18.2 | 1180 | 113.8 |

| | | | | |
|---|---|---|---|---|
| 2020 | 83.6 | 18.1 | 1210 | 125.4 |
| 2021 | 84.7 | 19.2 | 1250 | 146.9 |
| 2022 | 85.3 | 19.9 | 1325 | 189.0 |

**Table 3**. Data of the target parameter by years.

| Years | Number of Graduated Physical Education Teachers |
|---|---|
| 2014 | 2431 |
| 2015 | 2635 |
| 2016 | 3028 |
| 2017 | 3036 |
| 2018 | 3326 |
| 2019 | 3489 |
| 2020 | 3728 |
| 2021 | 4156 |
| 2022 | 4206 |

## 3. Results and Discussion

### 3.1. Forecasting the number of physical education graduates in Türkiye using artificial neural networks

Sports sciences faculties in Türkiye are experiencing an increase in GPET this year. The ANN was trained using a 4-8-1 architecture, using input factors that influence GPET, including population, student count, educational allowances for instructors, and the budget of MNE. The parameter data encompass the years 2014 to 2022. The LM method and BR algorithm were employed to ascertain GPET in Türkiye, with the estimation findings for 2023 and 2030 presented in Figure 1. The LM algorithm is a data-driven computational approach particularly applicable when the connection between model input and output parameters is non-linear (Nguyen-Truong & Le, 2015). The LM method partitions the dataset into 60% for training, 20% for validation, and 20% for testing. The BR algorithm can analyze intricate data sets and differentiate between dependent and independent variables in complicated, non-linear interactions (Shaik et al., 2021). The BR method established the clustering rates at 60% for training, 20% for validation, and 20% for testing. The ANN forecats were compared with two distinct chosen methods. The LM algorithm forecasted GPET in 2030 at 5115, with an $R^2$ value of 0.98152, but the BR method assessed GPET to be 5030 in 2030. $R^2 = 0.98892$. Table 4 displays additional performance metrics for GPET values, including MSE, RMSE, SSE, and MAPE. According to DrDataStats (DrDataStats, 2024), the GPET for 2022 was 4206, with

projections for 2030 indicating a growth of 1.216 times according to the LM methodology and approximately 1.20 times according to the BR algorithm. In comparison to the two algorithms, LM showed the most significant rise in 2030 (Figure 2).

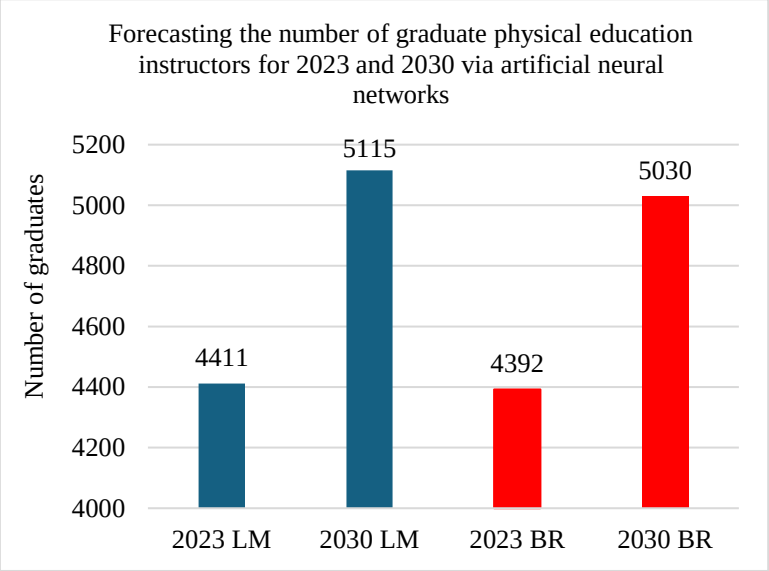


**Figure 2.** Forecast of physical education instructors graduation with Artificial Neural Network methods.

**Table 4.** Performance metrics of Artificial Neural Network methods.

| Algorithm/ Metrics | MSE | RMSE | SSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| Levenberg-Marquardt | 18,401 | 136 | 165,604 | 2.55 | 0.9466 |
| Bayesian Regularization | 8135.1 | 90,2 | 73,216 | 2.41 | 0.9764 |

### 3.1.1. Sensitivity analysis

To ascertain the impact on the output parameter utilized in the models forecast for the GPET 2023-2030 in Türkiye, a sensitivity analysis was conducted on the input parameters. The Garson and Yoon algorithms were selected for sensitivity analysis. In 1991, scholars initially utilized the Garson method, which assesses feature significance based on absolute weight values (Garson, 1991). Scholars have increasingly favored the Garson algorithm as a strategy. Researchers assert that the connection weight method is the most effective means of ranking parameter significance (Olden et al., 2004). The Yoon method is characterized by the ratio of the variation of a certain input variable to the variations of all other input variables (Yoon et al., 1994). The Garson technique for sensitivity analysis of LM indicates that the

education preparation allowance parameter for instructors significantly influences the output parameter, while the population parameter has the least impact. The Yoon algorithm noted a similar phenomenon. The sensitivity analysis for BR, using the Garson technique, identifies the population parameter as the input parameter with the least impact on the output parameter, while the number of students has the most influence. The Yoon algorithm yielded results comparable to those of the Garson algorithm. Figure 3 presents the sensitivity analysis data for the LM method, whereas Table 4 displays the sensitivity analysis data for the BR algorithm.

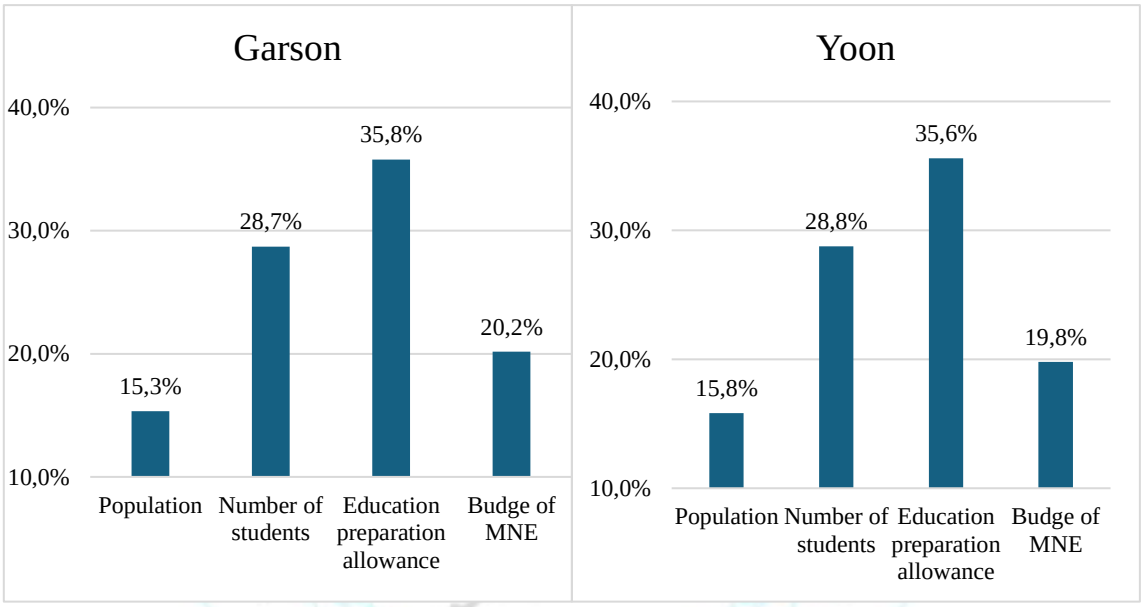


**Figure 3.** Sensitivity analyses of input parameters for the Levenberg-Marquardt algorithm (Ministry of National Education).

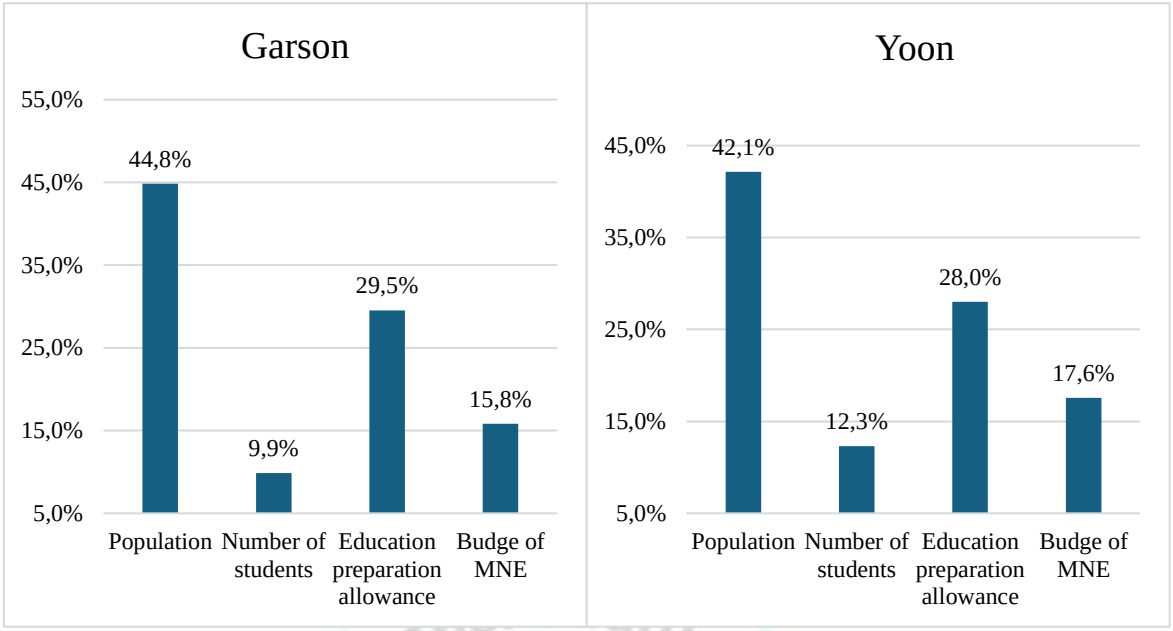


**Figure 3.** Sensitivity analyses of input parameters for the Bayesian Regularization algorithm (Ministry of National Education).

### 3.2. Forecasting the number of physical education graduates in Türkiye using ARIMA

Türkiye used ARIMA models for GPE forecasting. To achieve this, GPET data was graphically represented as a year vs. graduate number chart utilizing the SPSS23 software for each year from 2014 to 2022. Subsequently, the parameters p, d, and q were identified for the ARIMA models, leading to the formulation of the models and execution of estimations. Initially, the 0,1,0 model was developed. According to DrDataStats (DrDataStats, 2024), GPET is expected to receive the designation 4206 in 2022. The projection for the 0,1,0 model by 2030 indicates that GPET will expand by about 1.66 times relative to 2022. The subsequent model was established with p, d, and q variables set at 0, 1, and 1, respectively. The developed model indicates that while there is an estimated 1.43-fold increase in GPET compared to 2021 for the year 2030, selecting a q value of 1 relative to the previous model resulted in a decrease in the 2030 forecasted. Another ARIMA model with p, d, and q values set at 1, 1, 1, forecasts a 1.3718-fold increase in GPET for the year 2030 based on the 2021 estimation. However, this estimation reflects a decline compared to the ARIMA (0, 1, 0) model, attributed to the escalation of the p, d, and q values. By decreasing the q value, the 1,1,0 model of the alternative estimate framework, ARIMA, demonstrates an increase compared to the 2030 estimation of the ARIMA 1,1,1 model. The ARIMA 1,1,0 model for 2030 was assessed, and GPET rose by roughly 1.46

times relative to 2021. Among the four distinct ARIMA models, the (0,1,0) configuration generated the highest number of forecasts for 2030, whilst the (1,1,1) arrangement produced the fewest. Figure 5 presents the ARIMA model predictions for 2023, while the figure 6 depicts those for 2030. Table 5 presents additional model performance metrics (MSE, RMSE, SSE, and MAPE) for GPET values.

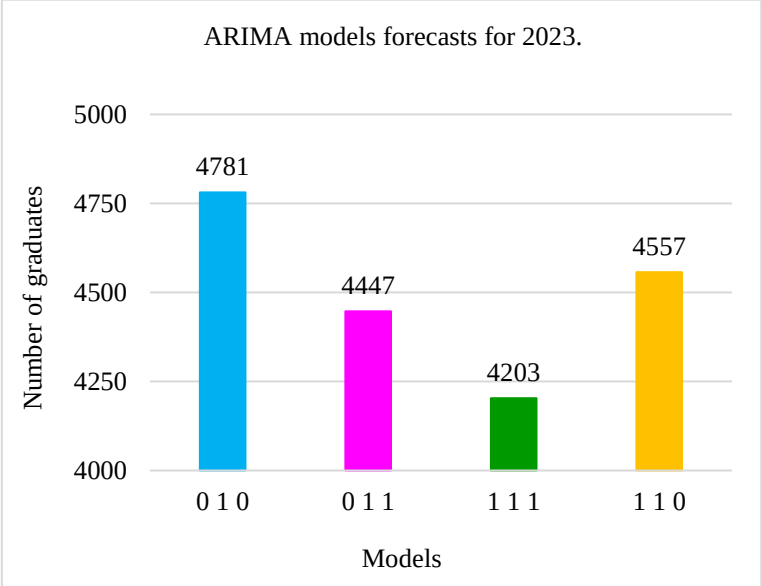


**Figure 5.** Forecast of the number of physical education teachers who will graduate in 2023 using ARIMA models.

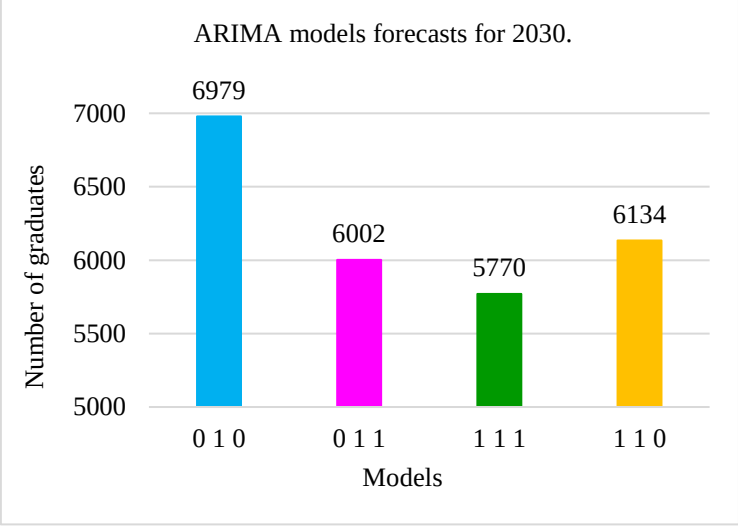


**Figure 6.** Forecast of the number of physical education teachers who will graduate in 2030 using ARIMA models.

**Table 5**. Performance metrics of ARIMA models.

| Models/ Metric | MSE | RMSE | SSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| 0 1 0 | 22,253.5 | 149.2 | 200,281.3 | 3.3 | 0.9280 |
| 0 1 1 | 12,358.8 | 111.2 | 111,228.9 | 2.2 | 0.9700 |
| 1 1 1 | 13,261.8 | 115.2 | 119,356.4 | 2.2 | 0.9700 |
| 1 1 0 | 14,779.2 | 121.6 | 133,013.4 | 2.6 | 0.9600 |

### 3.2. Forecasting the number of physical education graduates in Türkiye using Holt-Winters

The HW approach was employed to project GPET in Türkiye from 2023 to 2030. According to DrDataStats (DrDataStats, 2024), the GPE was 4206 in 2021. The HW method's projection for 2030 indicates a 1.4350-fold increase relative to the amount reported in 2021. Figure 7 presents the projected statistics for 2023 and 2030. Table 6 presents the performance metrics of the HW approach-developed model.

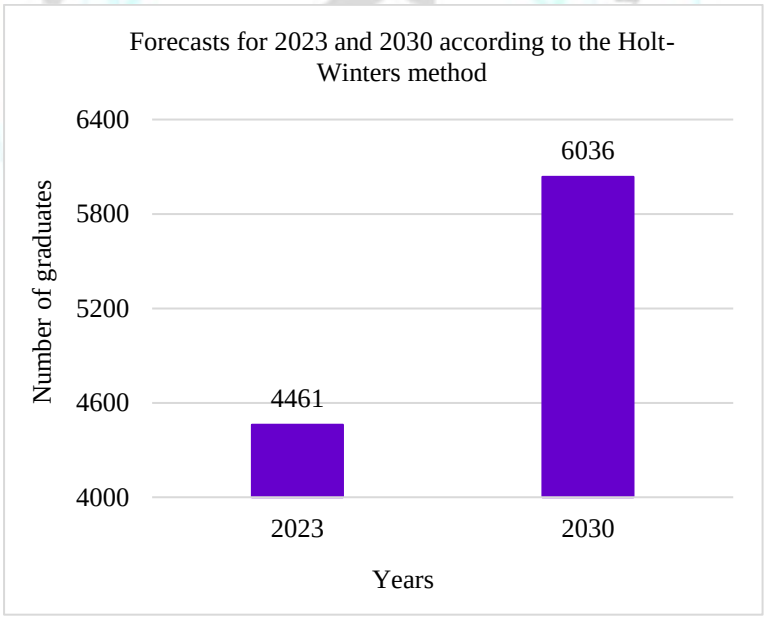


**Figure 7.** Forecast of the number of physical education teachers who will graduate using the Holt-Winters method.

**Table 6.** Performance metrics of the Holt-Winters method.

| Method/ Metrics | MSE | RMSE | SSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| Holt-Winters | 10,391.8 | 101.9 | 93,525.9 | 1.9 | 0.9800 |

Figure 8 shows Türkiye's actual GPE values from 2014 to 2022, as well as the estimation methodologies projected for 2023 to 2030. Among the estimating approaches, ARIMA 0, 1, 0 forecasted the greatest GPET value for 2030, whilst the BR algorithm projected the lowest GPET value. The model exhibiting the most significant growth from 2023 to 2030 was identified as ARIMA 0, 1, 0, with an increase of 2198 individuals.

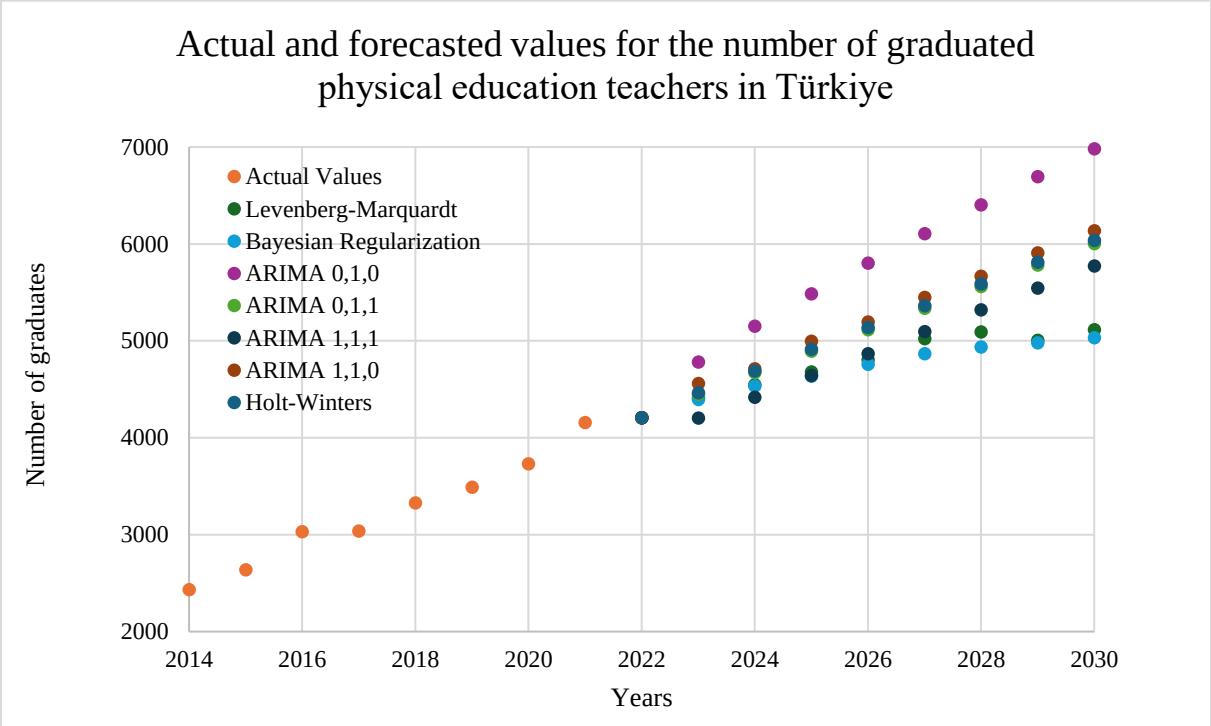


**Figure 8.** Actual figures for the number of graduated physical education teachers in Türkiye from 2014 to 2022, with forecasted figures for the number of graduated physical education teachers from 2023 to 2030.

## 4. Results

Türkiye is classified as a developing nation with a significantly large youth demographic. This requires focusing on sports and infrastructure. Identifying school-aged children and adolescents, guiding them towards sports and athletic disciplines, and monitoring their athletic growth should be fundamental responsibilities of physical education instructors. To cultivate athletes at both national and global levels, efforts must begin at the foundational level, specifically the infrastructure, thereby underscoring the significance of physical

education instructors during the school years. Medals and trophies should not be the sole measure of success in sports. Achievement in sports significantly enhances a nation's economy, tourism, and promotional advertising. Artificial intelligence is becoming increasingly important due to technological advancements. Artificial neural networks and time series, both subfields of artificial intelligence, are highly successful at forecasting future events. This research projected the number of physical education instructors expected to graduate by 2030. Although the ARIMA 0, 1, 0 model from the time series yielded the most accurate predictions, the ANN's BR algorithm produced the least accurate results. These estimation results will assist policymakers and inform feasibility reports as needed. The assessment of physical education instructors graduating in the next years is crucial for the training of future athletes and the historical accomplishments of our nation, and it is believed that an original study has been conducted based on the author's expertise.

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