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Using a Deep Neural Network Model to Forecast Population Dynamics in Iran

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ABSTRACT

Iran has undergone unique demographic changes in recent decades. This paper aims to project the Natural Population Growth rate (NPG) over the next decade (2024–2034), offering a comprehensive perspective on the future of Iran's population dynamics. In this regard, to accomplish the above task, this work deals with the projection of most important demographic measures that characterize the population process, namely the Crude Birth Rate (CBR), the Crude Death Rate (CDR), and the Population Doubling Time (PDT).

To this end, a deep neural network modeling approach was developed and applied. Deep neural network forecasting is one of the most important and influential techniques in machine learning and artificial intelligence. The data-driven model, based on data from the Statistical Center of Iran, was implemented in MATLAB.

Results from the paper indicate that the CBR drops from 11.3 per thousand in 2024 to 9.3 per thousand in 2034. On the other hand, the CDR increases from 5.2 per thousand in 2025 to 6.1 per thousand in 2034. As a result, the NPG is projected to decrease from 6.1 per thousand in 2025 to 3.2 per thousand in 2034. Lastly, PDT for the population is forecasted to rise from 114 years in 2025 to 218 years in 2034.

This study presents a deep neural network model to describe and forecast the complex dynamics of population change in Iran. Constructing this model helps policy-makers and planners use the forecasted population dynamics to design and implement programs and policies with greater precision.

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1. Introduction

During the past decades, Iran has gone through an era of striking economic and social developments. This development has brought about changes in the size, structure, and dynamics of Iran's population. Today, population growth is among the pivotal policy focuses in Iran, accompanied by many opportunities and challenges. Notably, population growth is one of the most important statistical indicators for any country, playing a major role in various areas of economic and social planning. These indicators are directly influenced by different variations in the dynamic demographic components of fertility, mortality, and migration (Kazemi-Pour, 2010).

The analysis of available statistics and information shows that Iranian population has undergone significant changes during the past one hundred years. During the decade 1966–1976, Iran’s population grew at a rate of 3.1 percent. With the start of family planning programs in the second half of the 1980s, this growth rate fell to 2.7 percent in the decade 1986–1995. Then, during 1996–2006, due to demographic echoes from the post-revolution and post-war periods, this rate reached its highest level in Iran’s demographic history, about 3.9 percent (Esmaeili, 2025; Razeghi –Nasrabad et al, 2025).

Consequently, when the government developed policies, which included expanding the rural health network, developing low-income regions, and raising education levels—especially among women—and aligned development and health programs with family planning, infant mortality declined, reducing the demand for a large number of children. The yearly population growth rate fell to approximately 1.9 percent in 1986–1996, then to approximately 1.6 percent in 1996–2006, and again to about 1.3 percent in the five-year period from 2006 to 2011. For 2011–2016, population growth decreased even further to 1.24 percent (Fathi et al., 2022). This rate now stands below one percent today (Esmaeili & Abbasi-Shavazi, 2024). The population growth rate reached 0.76 percent in 2023. (Torkashvant-Moradabadi & Irannejad, 2024).

Factors that have contributed to the reduction in Iran's population growth over the last two decades include increasing literacy and education levels, particularly among women; urbanization; industrialization; increased cost of living; and changes in attitudes and preferences of families—

especially young couples—towards fewer children. Improvement in health and reduction in the rate of mortality, particularly infant mortality, have resulted in increased life expectancy, and all these form part of the demographic transition stages of Iran (Fathi et al., 2022).

The low rate of population growth can bring about numerous other economic, social, and cultural consequences on the entire society. Some of the economic effects might include low per capita income and reduced supply of labor, leading to higher taxes on the employed section of the population, according to Mino & Sasaki, 2023. This might lead to lower growth of GDP or even its contraction, therefore increasing the recession risks of the overall economy. Another notable effect of a lower population growth rate is an increased dependency ratio, which exerts further burdens on the labor force; this may lead to an elderly care crisis and problems financing social support programs due to a higher proportion of retirees to workers.

The decline in the population can affect military strength, influencing factors of national security. It can exacerbate mental health issues and inflation pressures associated with aging (Friedman, 2020).

Understanding the rate of population growth, together with other economic and social indicators, is a fundamental necessity for planning national development. Projections of a society's basic needs depend on population-related statistics since population and its past, present, and projected developments are among the most important variables used in planning. The estimation of future population is of great importance because core population data come from Population and Housing Censuses carried out every five to ten years (Fathi et al., 2022).

Various methods have been used to forecast population to date, and researchers such as Booth (2006), Wilson (2011), and Land (1986) have categorized these methods. In this classification, the methods are grouped into the following categories: cohort-based methods, regression methods, time-series-based methods, expectation-based methods, and simulation methods. For instance, the cohort-based method forecasts population counts and sex-age survival ratios, birth counts and birth rates, mortality, and migration, but it faces challenges of uncertainty in probability assessments and the flexibility of assumptions. The regression method, which relies on fitting a curve to past data in order to model the structural details of the population along with the implications of mortality, birth, and migration, has inefficiencies related to efficiency and flexibility as well (Azarfar et al., 2017). In this approach, the population size is projected by using historical independent variables, and a curve is fitted to the historical population data. The method has its challenges because it fails to represent the detailed structure of the population; moreover, it cannot model mortality, birth, and migration rates straightforwardly (Azarfar et al., 2017).

Time-series analysis-based or interpolation-based methods are the most common approaches in population forecasting. At the same time, by constructing a system which behaves like the real system, simulation methods reflect the behavior of the real system in a simpler and virtual way (Nigri et al., 2022). Rafaftery & Sevcikova (2023), in a paper titled "Probabilistic population forecasting: Short to very long-term," present a new approach for estimating future population sizes and characteristics that is grounded in probabilistic models. Their results show that probabilistic population forecasting, as a precise approach, is an effective tool in analyzing and predicting population developments. With an emphasis on flexibility and focusing on uncertainty, this approach is recognized as a useful tool for both short-term and long-term planning. Among them, the probabilistic forecasting method was based on deep neural network modeling and also discussed as one of the most innovative intelligent methods in probabilistic forecasting and data analysis in population projections (Esmaeili & Abbasi Shavazi, 2024). Deep neural networks are among the most important and influential technologies in the field of machine learning and artificial intelligence. These networks, like biological neural networks, help in processing and analyzing data (Folorunso et al., 2010; Martinez-Ramon et al., 2024).

It is an intelligent approach with complex structures that can learn nonlinear and complicated patterns. The advantage of this technique is mainly involved in handling large quantities of data with multi-variability in features. Deep neural networks are capable of identifying and learning complex nonlinear patterns-a feature considered crucial for accurate and optimal forecasts (Torabi & Esmaeili, 2021). In addition, the network greatly adapts to changes in input data and their nature; thus, finding applications in many areas. Deep neural networks greatly enhance predictive accuracy with multiple nonlinear layers instead of traditional methods such as regression or linear models. They work well on large and complex datasets with a great number of features, drawing out important patterns and trends from vast amounts of data (Grossman et al., 2023; Modis, 2002).

This research utilizes the unique features of deep neural networks in the forecast of population dynamics in Iran. The key goal of this paper is to forecast the Iranian natural population increase growth rate for the next ten years. To achieve this, forecasts of some of the most important population change indicators are considered, crude birth rate- CBR, crude death rate-CDR, and the population doubling time- PDT. For this purpose, data on births and deaths that have a time-series structure annually over a period of 60 years from 1965 to 2024 were used, obtained from the Statistical Center of Iran (Statistics Center of Iran, 2025). It is important to mention here that in the case of the forecast of the rate of natural population growth- NPG, demographic characteristics are taken into consideration but migration flows are not included; therefore, the migration effect on the dynamics and changes of the population is excluded from the calculations.

2. Literature review

In the review of related literature, considering the focus of our study on predicting population growth using deep neural networks, we first look into research that applies deep neural networks in the prediction of population growth. Acknowledging that artificial intelligence tools provide a robust platform for data analysis and prediction, we then evaluate the analysis of the outputs of models using neural networks from a demographic perspective in light of the implications and consequences of population growth. Finally, we summarize the material discussed.

The next literature review examines deep neural network–based intelligent modeling, representing the recent trend in population growth prediction. According to Mansour et al. (2025), in their article titled "Predicting Population Growth in Libya Using Deep Learning Techniques (LSTM)," the model has shown remarkable accuracy and presents a major tool for policymakers and planners.

Nwozor & Onoseraye (2025), propose an optimized machine learning model using an artificial neural network coupled with a genetic (neuro-genetic) algorithm for population growth prediction. They state that accurate population forecasting is required for economic and national development, while the results obtained from the proposed model indicate higher accuracy than those in previous studies. Mustapha et al. (2024) apply a recurrent neural network with LSTM units to forecast the population of each Nigerian state. In general, their findings indicate that deep learning and other smart technologies may handle complex societal problems and improve the current approaches to population estimation.

This section reviews literature on the implications of declining population growth. Kreager, (2019) discusses population growth in terms of various thematic frameworks and historical demographic literature, placing growth within rich historical contexts and highlighting interdependencies between economic, social, and environmental factors. The review argues that insights into historical patterns of population growth can be used to develop policies and strategies for demographic challenges like aging and urbanization. The paper offers an overview of the literature with a scholarly synthesis on how historical perspectives help explain contemporary demographic problems.

Moheby-Meymandi et al. (2023) discussed the population growth of Iran, changes in age structure, and their economic consequences and presented their findings. This study indicates that both phenomena of population growth and aging structure change are significant results of demographic transition. Proportional events _ a phenomenon where both the size and age distribution of a population are impacted at once _ show how overpopulation and demographic shifts affect the demographic dynamics in Iran. These findings raise the need for considering age structural change and its economic consequences within the country's planning and policymaking.

This is what Danesh & Yekdast have concluded in the paper "Reducing Iran's Population Growth Rate and Its Effects on the Country's Power and National Security" in 2023. A sustained reduction in population growth may lead to demographic imbalance, a shrinking youth and skilled workforce, a weakened defense force, and consequently, reduced national power and security.

The literature review above shows that, particularly among intelligent methods, neural networks and deep learning techniques achieve remarkable accuracy and efficiency in population growth trend prediction. They can handle incomplete and complex data and generate long-term predictive trends with high efficiency. Compared to other traditional methods, the intelligent models perform very well in maintaining high accuracy and reducing errors significantly, and they play important roles in population policymaking and planning.

Existing literature reviews prove that declining population growth has far-reaching economic, social, and cultural implications. Among these are lower per capita income, a decrease in the labor supply, higher taxes on working people, and stagnation of economic growth. Added to these are the rising dependency ratio and challenges associated with elderly care financing for supportive programs, given the dramatic drop in the ratio of working-age versus retired people. A decline in the population growth rate ages the population, increases labor shortages, and heightens general dissatisfaction, which, in turn, can further lower birth rates. Hence, understanding the trends and implications of population growth assumes both relevance and urgency. Within this context, the current paper presents a forecast of Iran's natural population growth rate using modern intelligent methods, especially deep neural networks, based on the capabilities identified in the literature, so as to provide a more complete and detailed view of the future demographic situation in that country.

3. Data and Methods

These are birth and death records obtained from the Iran Civil Registration Organization, which are submitted to the Statistical Center of Iran for publication (Statistical Center of Iran, 2025). These data constitute an annual time series spanning 60 years, from 1965 to 2024. In 2024, the number of births is recorded at 979923, while deaths in the same year are recorded at 458848 (National Organization for Civil Registration, 2025). These statistics have been announced by the

Iran Civil Registration Organization. However, this data has not yet been submitted to the Statistical Center of Iran for publication. The first step in projecting the natural growth rate is to predict the crude birth rate over the next ten years, followed by the projected crude death rate. Then, by calculating and projecting the difference between the crude birth rate and crude death rate, the natural growth rate of the population is determined, and its trend is forecasted. After having this rate, the time that will be required for the population to double in Iran will be predicted. A deep neural network-based modeling approach will be used for projecting the trend of the natural growth rate and the changes taking place in the population of Iran. Deep neural networks are among the most important and influential technologies in the area of machine learning and artificial intelligence. These networks process the data and analyze them, just like biological neural networks (Martinez-Ramon et al., 2024; Mahmoudian & Esmaeili, 2023).

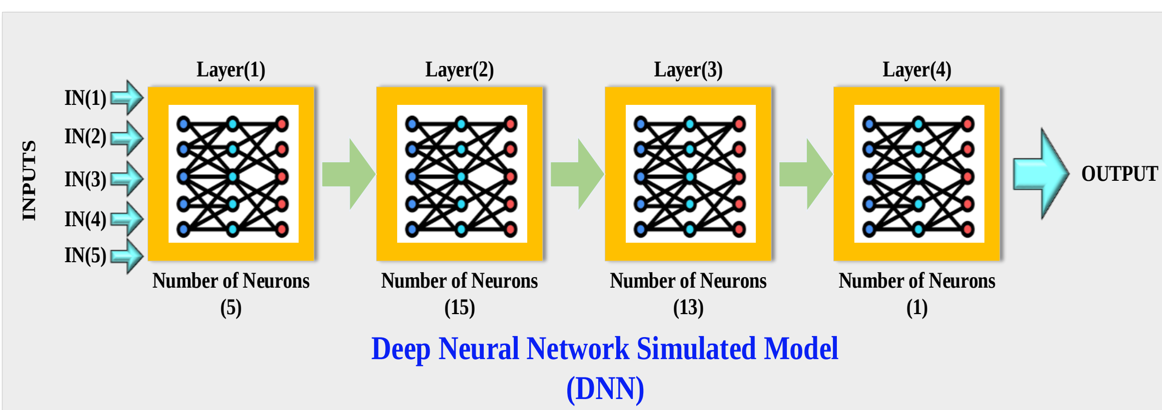
Deep neural network modeling is an intelligent approach that utilizes complex structures such as convolutional and recurrent networks to spot patterns and relationships within data. These networks include an input layer, hidden layers, and an output layer; the raw data are fed to the input layer; in the hidden layers, feature extraction and data processing are performed, while the output layer gives the final result, including predictions or classifications. Training the model is one of the most important phases of the whole procedure, where labeled data learn the features; this process involves defining the loss function, updating weights using algorithms such as gradient descent, and tuning model parameters. Data pre-processing and tuning of parameters contribute significantly toward improvement in performance. After training, using test data, the model gets ready for deployment in order to predict new data. Summing it up, this process requires extensive knowledge in algorithms, architectures, and pre-processing to make any identification and analysis of complex patterns in data (Goodfellow et al., 2016).

4. Mechanism and performance of the model

The required data to develop a predictive deep neural network-based model have been extracted from 60 years of data maintained by the Statistical Center of Iran. Section Three of the articles describes them in detail. The input data for training the neural network model have fallen into three categories.

- **Inputting data into the neural network in order to train the model**: During the data modeling process, the first step involves the preparation of input data, which is considered a crucial element when it comes to training the deep neural network. During this stage, the data are divided into two categories, with the first category consisting of 70 percent of the data used for the training of the neural network, while the remaining 30 percent will be used in testing the model.
- **Construction of the Model**: The model is built and trained using the data coming from the first step. It is one of the most sensitive steps in model development. The number of layers in the neural network, the number of neurons, and the training function to be used in MATLAB should be selected and specified according to the input data and the required accuracy of prediction. Then, after finding out the specifications of the model and its structure, the training will be performed using the input and output data. In the present article, a four-layer deep neural network is used, which includes five neurons in the first layer, fifteen neurons in the second layer, thirteen neurons in the third layer, and a single neuron in the final layer, as shown in Figure 1.

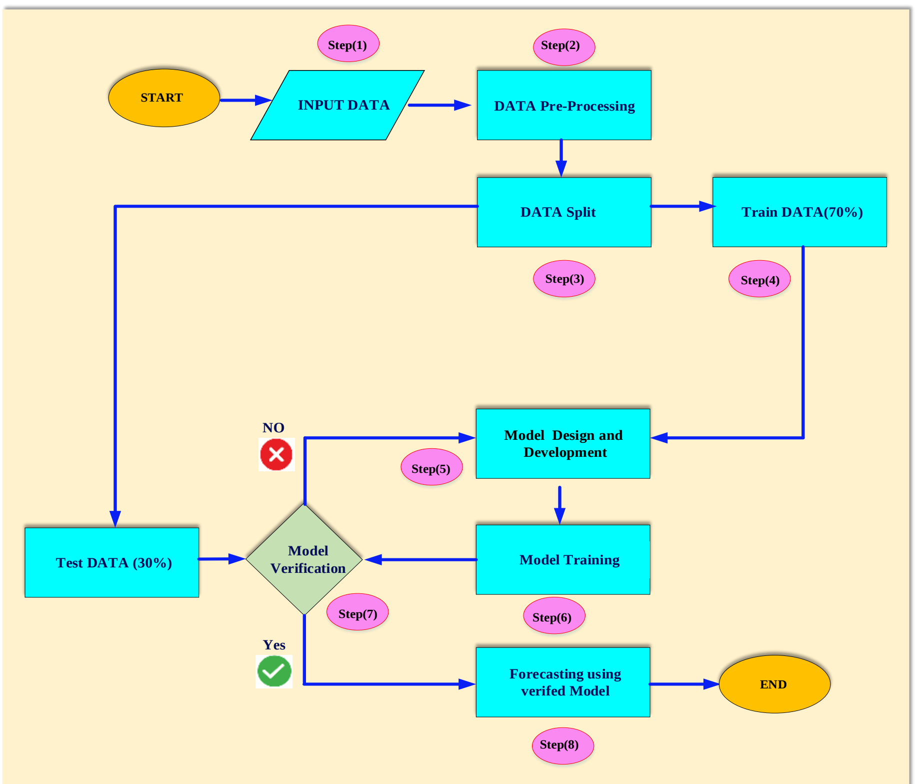
Figure 1: Overall structure of the designed DNN



Note that the number of neurons in each layer and the number of layers were chosen based on tests of different configurations, balancing computational load and minimizing training error. More layers increase computational burden and make model tuning more difficult; if the number of layers is too small, accuracy in results decreases. As a result, an optimal state was selected based on successive simulations and running the model. To train the model in this article, the data for the year 2024 were used as the output, and the data from five years prior were used as the input to train the deep neural network. In the next training step, a backward step was taken, using the information from the year 2023 as the output and the data from five years earlier as the input to retrain the deep neural network. In this step-by-step technique, modeling errors are reduced due to the use of more data and the ongoing training and learning of the network at each step. In other words, through an iterative loop and the trained neural network model, forecasting can be done gradually year by year. Intelligent algorithms available in MATLAB have to be used during neural network training in order to estimate the parameters of the input–output connector functions of the neural network. It is relevant to note that the present article, after determining the structure of the network, undertakes to train the model using the training data, encompassing updating weights using optimization algorithms.

- **Prediction based on the trained model:** In the current study, prediction over a ten-year horizon was carried out using the model designed from the training data. It is noteworthy that the accuracy of the model was verified during the previous step using results from the test data. In particular, the Coefficient of Efficiency for the test dataset was the main criterion. To be more specific, this index considers the difference between the values of the real test data and the values predicted for the respective test period, which shows how well the model is able to estimate real data. Provided the above-referenced criteria regarding the validity of the model, coefficient values over 90% present satisfactory performances while values lower than 80% present poor ones (Cimen & Kisi, 2009). In the context of the current study, the coefficient of interest was equal to 93.75%, which implies high reliability and predictive competence of the deep neural network and the performance was evaluated as satisfactory. The steps of designing and implementing the model are presented step-by-step in Figure 2 in the form of a flowchart. The data go through preprocessing after entering the model, as indicated in Figure (2), and are then divided into training and testing sets. The model is then specified and trained using the training data. The testing data are used for validation to measure performance. If it meets the validation criteria, it proceeds to the end of forecasting. If not, the model is redesigned and retrained. This continues until the validation criteria are satisfied and it is done with forecasting.

Figure 2: A flowchart describing the algorithm utilized for model development



5. Evaluation of the data

In this section, we first assess birth data and then mortality data. To analyze and evaluate the data, we compared statistics reported by the Statistical Center of Iran with numbers published in different yearbooks and other reliable sources. The review indicates that, with the exception of a few, statistics of deaths registered and births recorded, which are used in this study, are in agreement with the data published elsewhere.

In the time-series table of birth data, it can be seen that the number of births in 2004 decreased significantly compared with preceding years. For the investigation of the 2004 birth data, several sources were considered. According to a paper published by the Population and Information Office in 2009, the accuracy of the registered birth data was checked for 2004. It has also been shown in this study that total birth figures were revised from 961572 to 1154368 (National Organization for Civil Registration, 2010).

To validate the mortality data from 1971 to 1991, we referred to Zanjani (1993). That study reported that the information utilized in this research is completely compatible with Zanjani's data. However, Zanjani states that, despite the considerable improvement in death registration in Iran, it is still incomplete. The number of deaths in 2004 seemed implausible and was reported as 295427 (167621 men and 127806 women). After performing the necessary investigations, it was concluded that these numbers refer to deaths that occurred between April and January of that year. As such, we investigated various sources of mortality statistics. We accessed the website of the Statistical Center of Iran and determined that the yearbook of 2006 published the data on mortality for the year 2004, and this was also available in a paper published by the Population Registry Office in the Journal of Population. We then used these two sources to determine that the number of registered deaths for that year was 355 213 (201306 men and 153907 women), and thus the data for this year were corrected. Statistics on registered deaths for 2006 and 2007 show minor discrepancies with the 2006 Yearbook, which can be disregarded. The registered deaths in 2011 are different depending on the source. The available information presents 372797 registered deaths (206845 men and 161448 women), but the Yearbook for 2011 shows 422133 deaths

(228636 men and 193451 women). Also, in the statistical yearbooks from 2014 to 2019, the registered deaths for 2011 were reported as 383504 (214707 men and 168750 women), which in this study will be used as alternative information and as corrections.

According to data from the Civil Registration Organization, the number of registered deaths in 2018 was 376929. However, in the statistical yearbooks for 2019 and 2021, the number of deaths reported was 377245 (211518 men and 165675 women). In the tables cited, the number of deaths registered in 2019 and 2020 showed minor differences compared with the 2021 Yearbook; hence, the latter was used as the reference source for these years as well, and these values were corrected (National Organization for Civil Registration, 2021).

6. Results

The objective of this study is to forecast Iran's natural population growth rate for the years 2024–2034. To achieve this goal, we first compute the crude birth rate and the crude death rate. It should be noted that because crude rates relate to the entire population, they do not provide detailed insight into a society's current status. Thus, the most important application of crude birth and death rates is estimating natural population growth. (Sarai, 2011).

This study's findings are presented in four sections. Section 1 forecasts the crude birth rate of Iran during 2024–2034. Section 2 provides a projection of the crude death rate within the same period. Section 3 is devoted to establishing the trend of natural population growth in Iran within 2024–2034. The forecast of the time that would be taken by the population to double within this interval is covered under Section 4.

In this paper, the researchers attempt to project the natural growth rate of the population in Iran for the years 2024–2034. To do so, we must first calculate the crude birth and death rates. As it is important to note, because the entire population is exposed to these phenomena, crude birth and death rates cannot provide detailed information on the actual conditions of a society. Thus, the main purpose of crude birth and death rates is to estimate the growth of natural population increase (Sarai, 2011).

6-1. Forecasting Crude Birth Rate- CBR in Iran for 2024–2034 using Deep Neural Network- DNN modeling

In this section of the paper, the CBR index for Iran will be predicted up to 2034. This index answers the question: How many people are added to a country's population through birth per 1000 people of all ages? (Sarai, 2011). Shown in Equation (1) is the method for calculating the CBR index as a central index.

$$CBR = \frac{B}{P'} \times 1000 \quad (1)$$

In equation (1), B[1] represents the total number of live births and P'[2] denotes the population of all ages at mid-year[3].

As Figure 3 shows, the crude birth rate is expected to decline steeply from 2024 to 2034, decreasing from 11.36 births per 1000 people in 2024 to about 9.35 in 2034. In other words, the deep neural network model predicts that in 2034, approximately 9 births will occur per 1000 people[4].

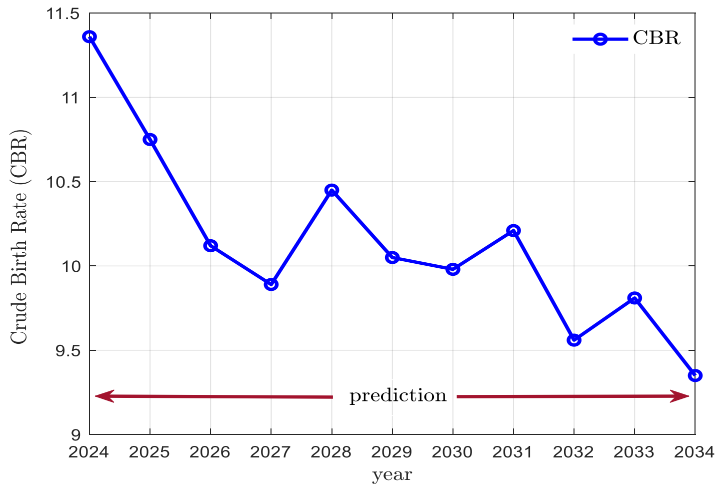
[1] Birth-B

[2] Population-P

[3] The mid-year population is calculated as the average of the population at the beginning of one calendar year and the population at the beginning of the next calendar year, i.e., the sum divided by 2 (Persa, translated by Seyyed Mirzaei, 1992; 151).

[4] Any incremental increases or decreases in the output of the model are based on information extracted from the training data, which was produced and plotted by a deep neural network within the MATLAB software environment.

Figure 3: Forecast of the CBR index in Iran for the years 2024–2034 based on DNN modeling.



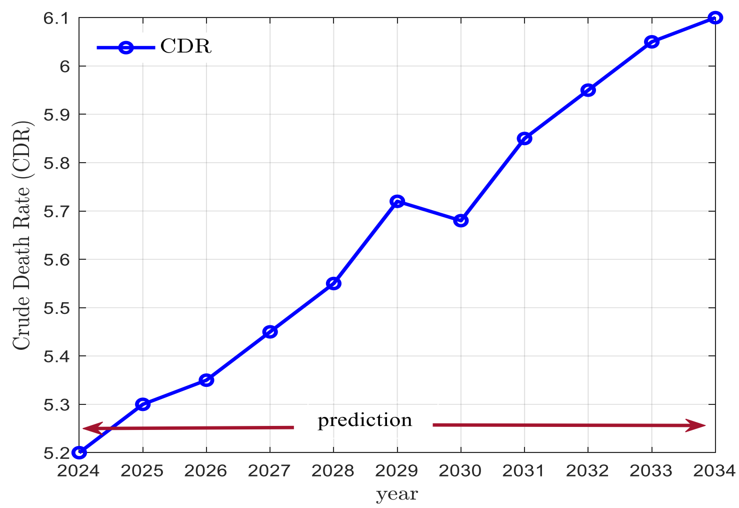
6-2. Forecasting Crude Death Rate- CDR in Iran for 2024–2034 using Deep Neural Network- DNN modeling

In this section, we project the CDR index for Iran through year 2035. This index measures the number of deaths per 1000 individuals in the total population across all age groups. (Sarai, 2011). The computation of the CDR index is presented in equation (2).

$$CDR = \frac{D}{P'} \times 1000 \tag{2}$$

Where D denotes the total number of deaths, and P' denotes the mid-year population of all ages. Figure 4 shows, via the deep neural network model, an upward trend in Iran's CDR over 2024–2034, rising from 5.2 to 6.1 deaths per 1000 people. Thus, the model estimates about 6 deaths per 1000 mid-year population due to mortality in 2034.

Figure 4: Forecast of the CDR index in Iran for the years 2024–2034 based on DNN modeling



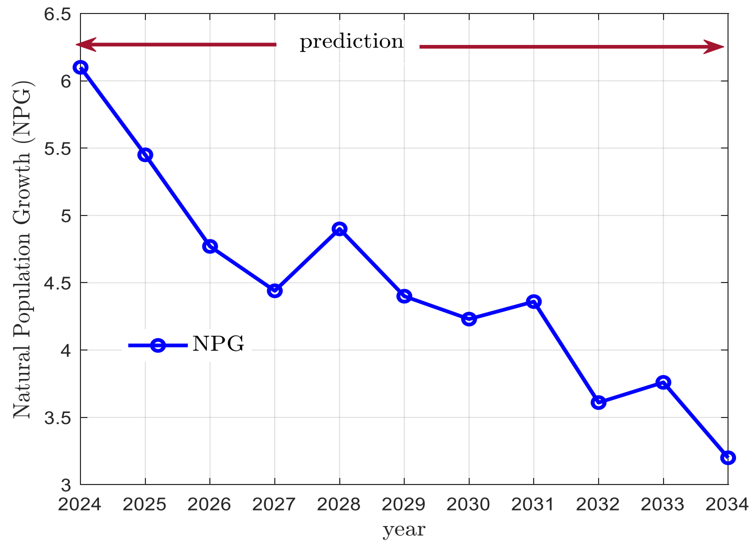
6-3. Forecasting Natural Population Growth- NPG in Iran for 2024–2034 using Deep Neural Network- DNN modeling

If no type of migration, whether internal or external, occurs in the population of a country, population change is determined only by natural factors, that is, births and deaths. The resulting change constitutes the natural increase of the population. One of the ways to calculate annual natural increase is to take the difference between the crude birth rate and the crude death rate (Amani, 2015). In this section, by using Amani's definition (2015), this indicator is calculated and forecasted up to the year 2034. The methodology for the calculation of this indicator is presented in Equation (3).

$$NPG = CBR - CDR \qquad (3)$$

Figure (5) shows that Iran's annual natural population increase rate is expected to decline significantly over 2024–2034, from 6.1 per thousand in 2024 to 3.2 per thousand in 2034. Consequently, the forecasted natural increase for 2034 is approximately 3.2 per thousand.

Figure 5: Forecast of the NPG index in Iran for the years 2024–2034 based on DNN modeling



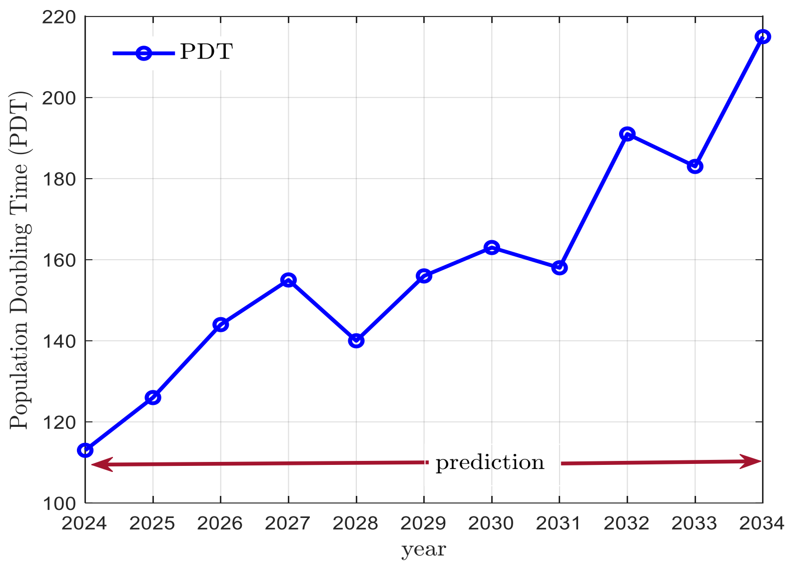
6-4. Forecasting Population Doubling Time - PDT in Iran for 2025–2034 using Deep Neural Network- DNN modeling

In this section, we will predict Iran's population doubling time for the period 2025 to 2034. Considering the natural increase in population, the population doubling time - PDT can be calculated using Equation (4), and the necessary results will be extracted. The population doubling time formula is presented in Equation (4), following the definition provided by Amani (2015; 47).

$$\mathbf{PDT} = \frac{\ln 2}{\mathrm{NPG}} = \frac{0.69315}{\mathrm{NPG}} \tag{4}$$

Figure 6, which shows the output of the deep neural network model, indicates that Iran’s PDT is expected to rise steeply over 2024–2034, increasing from 114 years in 2024 to 218 years in 2034. In other words, the model predicts a PDT of 218 years in 2034.

Figure 6: Forecast of the PDT index for Iran from 2024 to 2034 based on DNN modeling.



7. Conclusion

Demography is the study of the size, distribution, and composition of the population, which evaluates the dynamic elements that drive population change, such as fertility, mortality, and migration. These three components are intertwined and have shaped population change from the past to the present. Fertility and mortality are the major natural driving forces of population dynamics; the rates at which these vital events occur drive significant changes in societies. The consequence of the interactions is natural population growth. Consequently, in order to study natural population changes, one has to consider not only the timing of birth and death events but also their outcome, namely natural population growth.

Population growth, together with other economic and social variables, constitutes the basic foundation for national development planning. For example, forecasting a society's basic needs relies on population growth statistics, since the size of the population and its past, present, and projected changes are among the most important variables in the calculation of a plan. General censuses of population and housing, which are conducted every five or ten years, provide essential population information. Projecting populations for future years, therefore, is an important task that holds a special place in planning.

Long-term prediction problems need intelligent computer-based algorithms that could extract data patterns for future prediction due to the complexity of population dynamics. Consequently, computer-based modeling through programming has emerged as one of the pragmatic approaches in predicting demographic events. The current emergence is driven by continuous developments in information technology, hardware, and software that have made it feasible to develop software-based computational laboratories (Singh et al., 2015). A computer-implemented model is essentially a simulated system built from mathematical relationships using programming languages within software environments (Burch, 2003, 2018). It is a mathematical and logical descriptive model of a social process in which an attained goal characterizes the performance of this model during the modeling process (Esmaeili, 2023; Esmaeili et al., 2025; Abbasi-Shavazi & Esmaeili, 2020, 2022).

There has been growing interest in the use of intelligent systems in predicting variables within the social sciences. However, in demography, the adoption of these methods is relatively limited compared to other fields of study (Nigri et al., 2022; Torabi & Esmaeili, 2021). In this context, machine learning has given rise to a revolution in data science, which allows analysts to find nonlinear relationships among features and then predict new samples once they have been identified.

In this work, a four-layer deep neural network was used with 5 neurons in the first layer, 15 in the second, 13 in the third, and a single neuron in the output layer. This architecture, which refers to the number of neurons per layer and the total number of layers used, is chosen based on previous experimentation of several configurations with the aim of balancing the computational load with error in training. Increasing the number of layers raises computational demands and complicates model optimization, while too few layers can reduce accuracy.

The background necessary to design and train the network used for the prediction problem in this study is provided in light of the aim of this study, which is to forecast population changes in Iran, with a focus on natural population increase over the ten-year horizon 2024–2034. Two steps are followed to model the problem. First, we predict the crude birth rate and crude death rate based on sixty years of time-series data on births and deaths extracted from the Statistical Center of Iran, then use the rates to compute natural population growth. Second, with the information on natural population increase, we project the time required to double the Iranian population. These tasks will be done using different artificial intelligence techniques, including deep neural networks.

According to the deep neural network modeling, Iran's crude birth rate will face a downward trend in the next decade, from 11.36 births per 1000 population in 2024 to approximately 9.35 in 2034. On the other hand, the crude death rate is expected to soar in the same period, from 5.2 to 6.1 deaths per 1000 population. Consequently, the natural population growth will follow a comparative decline from 6.1 per 1000 population in 2024 to 3.2 per 1000 in 2034. Based on the model, the population doubling time will follow an upward slope, further extending from 114 years in 2024 to 218 years in 2034.

These projections must be viewed in perspective. Although the numerical models can be instructive, demographic changes are influenced by many factors that interact: behaviors, values, policies, technology, and economic and cultural conditions. In addition, unexpected events, such as armed conflict or other shocks, can change population trajectories dramatically, reinforcing the value of examining trends in combination with scenario analysis and uncertainty in forecasting.

The simulation results using deep neural networks show the expected decline in population growth in Iran over the next decade. With this in perspective, it is expected that policymakers and planners will pay more attention to strategies aimed at sustaining fertility levels and managing mortality through evidence-based programs. Such focused yet comprehensive policy development will help in further stabilizing and improving the country's demographic trajectory toward achieving sustainable demographic goals and a better quality of life.

References such as Mino & Sasaki (2023), Kreager, (2019), Bloom et al. (2013), and Danesh & Yekdast, (2022) show that a decline in population growth may have overall significant impacts on the economic, social, and cultural dimensions of societies. This, in turn, can create a decrease in per capita income, reduced labor supply, enhanced taxes on employed individuals, and even macroeconomic downturns. The literature also stresses that declining population growth does not only negatively affect the labor force and production but also enhances pressure on the system of social protection and probably diminishes innovation and entrepreneurship capacity. Therefore, these findings underscore the importance for planners and policymakers of monitoring demographic trends and anticipating their implications. Therefore, a prediction of decreasing natural population growth in Iran during the next ten years contributes to a clearer perspective for planners and policymakers toward the population dynamics that may unfold in the future, and helps establish evidence-based decision-making and effective planning to combat demographic challenges ahead.

In general, there are some limitations and research suggestions for future research related to this paper, the most important of which includes a lack of time-series data on migration in Iran. Migration is one of the main population dynamic factors that play a significant role in changing the age and sex structure, annual population growth, and social and economic conditions in both origin and destination countries. (Sadeghi et al., 2021; Sadeghi &Hosseini –Milani, 2025) The increase in the rate of population movements affects the immigrant- and emigrant regions significantly. So, despite the fact that migration is an important component of demographic change, the absence of time-series data on internal migration made us perform the calculations assuming a closed population. According to the suggestions for future work, several intelligent approaches can be adopted for model development. To this end, random forests, ensemble models, and reinforcement learning can be applied, providing deeper insights into population-related issues. Thus, a hybrid study has been recommended in which several machine-learning–based approaches are applied together. This allows the researcher to compare results for different methods and examine the performance of each with respect to predictive error metrics. Moreover, the ensemble technique can be further employed to combine the powers of each single method to obtain more robust and accurate forecasts.

Declaration of Competing Interest

I declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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