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# Predicting population growth in Libya using deep learning techniques (LSTM)

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## Abstract

Predicting population growth is a crucial element in planning future resources and sustainable development. With rapid changes in global demographics, there is a growing need for robust and accurate forecasting models. This research introduces a model leveraging deep learning techniques to analyze historical and demographic data for predicting population growth. Specifically, the study implements a Long Short-Term Memory (LSTM) neural network to address the temporal dynamics of population data. Performance enhancements were achieved through advanced techniques, such as feature embedding and algorithmic optimization. The study also explores the challenges of population prediction in regions with fluctuating growth patterns and demonstrates the model's ability to outperform traditional methods like ARIMA. Results show that the proposed model achieves high accuracy, providing valuable insights for policymakers and planners. The integration of deep learning approaches highlights their potential to revolutionize population growth forecasting and support strategic decision-making.

**Keywords:** Population Growth Prediction; Deep Learning; Long Short-Term Memory (LSTM); Time-Series Analysis; Demographic Forecasting

## 1. Introduction

The Population growth is a key driver of social, economic, and environmental change. Understanding and predicting this growth is essential for effective resource allocation, infrastructure development, and long-term planning.[1] Traditional statistical models, while effective in some cases, often struggle to handle the non-linear and dynamic nature of population data, especially when considering factors such as migration, birth rates, and mortality rates.[2] In recent years, advancements in artificial intelligence (AI) have introduced new possibilities for predictive analytics. Among these, deep learning has emerged as a powerful tool for extracting complex patterns from large datasets. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are especially suited for time-series analysis, making them an ideal choice for modeling population growth trends.[3]

This study aims to build on existing research by utilizing LSTM networks to predict population growth with greater accuracy and reliability. By integrating historical data with demographic variables, the proposed model addresses the limitations of traditional methods and offers a scalable solution for global and regional forecasting needs.[4]

Long Short-Term Memory is an improved version of recurrent neural network designed by Hochreiter & Schmidhuber.[13] A traditional RNN has a single hidden state that is passed through time, which can make it difficult for the network to learn long-term dependencies.[14] LSTMs model address this problem by introducing a memory cell, which is a container that can hold information for an extended period.[5]

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LSTM architectures are capable of learning long-term dependencies in sequential data, which makes them well-suited for tasks such as language translation, speech recognition, and time series forecasting.[6]

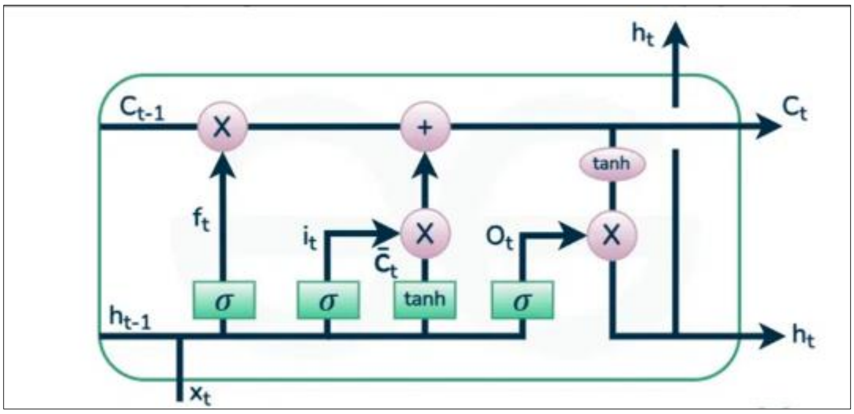


**Figure 1** LSTM

The information that is no longer useful in the cell state is removed with the forget gate. Two inputs xt (input at the particular time) and ht-1 (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias.[12] The resultant is passed through an activation function which gives a binary output.[7] If for a particular cell state the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use. The equation for the forget gate is:

$$ft=\sigma(Wf\cdot[ht-1,xt]+bf)\ ft=\sigma(Wf\cdot[ht-1,xt]+bf)$$

Where:
W_f represents the weight matrix associated with the forget gate.
[h_t-1, x_t] denotes the concatenation of the current input and the previous hidden state.
b_f is the bias with the forget gate.
σ is the sigmoid activation function.[8]

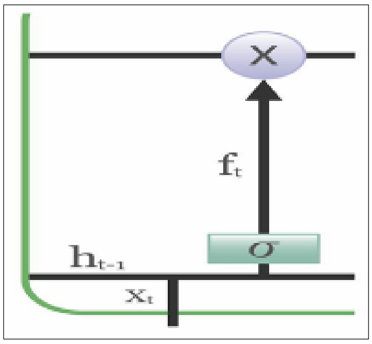


**Figure 2** Forget gate

## 2. Methodology

### 2.1. Data Collection and Preprocessing

Data was sourced from reliable global databases, such as the United Nations Population Division, alongside local and regional demographic statistics.[9] The dataset spans several decades to ensure sufficient temporal coverage. Key variables include:

- Demographic Factors: Age distribution, gender ratios, birth rates, mortality rates, and migration statistics.
- Temporal Trends: Yearly changes in population metrics to capture patterns over time.[10]

**Table 1** Population growth over 10 years in Libya

| Year | Population | Birth | Natural change | Emigration | Average age |
|---|---|---|---|---|---|
| 2011 | 6 188000 | 158 | 36 | 15.0 | 70.07 |
| 2012 | 5 870000 | 129 | 29 | 13.0 | 72.25 |
| 2013 | 5 985000 | 131 | 30 | 12.5 | 72.34 |
| 2014 | 6098000 | 134 | 33 | 12.3 | 71.51 |
| 2015 | 6 192000 | 131 | 34 | 11.9 | 71.70 |
| 2016 | 6 282000 | 129 | 34 | 11.5 | 71.76 |
| 2017 | 6 378000 | 127 | 34 | 10.9 | 72.48 |
| 2018 | 6 478000 | 125 | 34 | 10.5 | 72.79 |
| 2019 | 6 569000 | 123 | 36 | 10.4 | 72.46 |
| 2020 | 6 999000 | 132 | 39 | 9.6 | 72.4 |
| 2021 | 7092000 | 130 | 42 | 9.0 | 72.1 |
| 2022 | 7 179000 | 127 | 35 | 8.7 | 74.5 |

### 2.2. Preprocessing steps involved

- Data Cleaning: Removing inconsistencies, handling missing values, and standardizing formats.
- Normalization: Scaling data to ensure compatibility with the neural network's requirements.
- Feature Selection: Identifying the most relevant variables to optimize model performance.[11]

### 2.3. Model Architecture

The proposed model is based on an LSTM neural network due to its ability to capture long-term dependencies in time-series data.[15] Key features of the model include:

- LSTM Layers: Multiple layers to process sequential data and identify complex temporal relationships.
- Dropout Layers: Added to prevent overfitting and enhance generalization during training.
- Feature Embedding: Advanced embedding techniques to represent demographic variables in higher dimensions for better interpretability.

### 2.4. Experimental setup

- Data Partitioning: The dataset was divided into training (70%) and testing (30%) subsets to evaluate model performance.
- Loss Function: Mean Squared Error (MSE) was used to measure the discrepancy between predicted and actual values.
- Optimization: The Adam optimizer was employed to fine-tune model parameters efficiently.
- Tools and Libraries: The TensorFlow library, along with Python packages like NumPy and Pandas, was utilized for model development and analysis.

### 2.5. Evaluation Metrics

To assess model performance, the following metrics were considered:

- Prediction Accuracy: The percentage of correct predictions over a 10-year forecasting horizon.
- Mean Absolute Error (MAE): Measuring the average magnitude of prediction errors.
- Comparative Analysis: Evaluating the proposed model against traditional methods such as ARIMA.

## 3. Conclusion

Predicting population growth using deep learning techniques represents a significant advancement in the field of demographic forecasting. Traditional models, while useful for certain scenarios, often fall short in capturing the complex, non-linear relationships and long-term temporal dependencies inherent in population dynamics. By leveraging the capabilities of Long Short-Term Memory (LSTM) networks, this study demonstrates a robust approach to addressing these limitations.

The proposed model not only achieves high accuracy in predicting population trends over a 10-year horizon but also adapts effectively to regions with high variability and fluctuating growth patterns. This adaptability highlights the model's potential as a powerful tool for aiding policymakers, urban planners, and resource managers in making informed decisions.

Moreover, the use of advanced techniques such as feature embedding, dropout layers, and algorithmic optimization ensures that the model remains scalable and generalizable across diverse datasets and regions. The integration of deep learning into population forecasting opens the door to exploring additional variables, such as environmental factors, economic trends, and policy interventions, to create more comprehensive and actionable insights.

Future research could further enhance the model by incorporating real-time data streams, exploring hybrid approaches that combine deep learning with traditional methods, and extending the framework to include more granular regional and local-level predictions.

In conclusion, this study underscores the transformative potential of deep learning in solving complex challenges associated with population growth forecasting. By providing a scalable, accurate, and flexible solution, the proposed model sets the stage for more effective planning and sustainable development in a rapidly changing world. Through the results obtained, the results showed that the population growth rate in the coming years will be 1.6 % .

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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