

# Predicting Life Expectancy in Diverse Countries Using Neural Networks: Insights and Implications

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**Abstract:** Life expectancy prediction, a pivotal facet of public health and policy formulation, has witnessed remarkable advancements owing to the integration of neural network models and comprehensive datasets. In this research, we present an innovative approach to forecasting life expectancy in diverse countries. Leveraging a neural network architecture, our model was trained on a dataset comprising 22 distinct features, acquired from Kaggle, and encompassing key health indicators, socioeconomic metrics, and cultural attributes. The model demonstrated exceptional predictive accuracy, attaining an impressive 99.27% and an average error of 0.0034, underscoring the potency of deep learning in tackling complex, real-world challenges. Furthermore, our study delved into feature importance analysis, identifying critical determinants such as HIV/AIDS prevalence, income composition of resources, and socioeconomic status that significantly influence life expectancy. These findings provide actionable insights for healthcare policymakers and practitioners, emphasizing the importance of addressing health disparities, promoting economic development, and implementing targeted interventions. This research bridges the gap between data-driven methodologies and global health, offering a robust predictive tool and enriching our understanding of the multifaceted dynamics that shape life expectancy across nations.

**Keywords:** Prediction, ANN, Life expectancy

## I. Introduction:

Life expectancy is a fundamental measure of a population's health and well-being, serving as a crucial indicator for assessing the effectiveness of healthcare systems, economic development, and public policies.

Accurately predicting life expectancy in different countries is a complex task, influenced by a myriad of factors encompassing healthcare metrics, socioeconomic conditions, and cultural determinants.

In the pursuit of a deeper understanding of these intricate dynamics, this research endeavors to predict life expectancy using a neural network approach, drawing upon a meticulously curated dataset obtained from Kaggle. Comprising 22 distinct features, including variables such as Adult Mortality, GDP, Schooling, and HIV/AIDS prevalence, this dataset represents a diverse cross-section of 2940 samples spanning various countries and years.

Our predictive model, with a three-layer architecture (one input, one hidden, and one output layer), has been rigorously trained and validated, attaining a remarkable accuracy rate of 99.27% and an impressively low average error of 0.0034.

Beyond mere prediction, our study aims to unveil the most influential features that drive life expectancy variations. Through an extensive analysis, we have identified key factors such as HIV/AIDS prevalence, Income composition of resources, and socioeconomic status that significantly impact life expectancy outcomes.

These findings not only provide a powerful predictive tool but also contribute to a deeper understanding of the intricate interplay between multifaceted determinants and life expectancy, offering valuable insights for informed decision-making in the domains of public health and policy.

This research represents a substantial step toward harnessing the potential of neural networks in unraveling the complexities of life expectancy prediction and underscores the significance of interdisciplinary approaches in addressing critical global health challenges.

## II. Previous Studies:

Predicting life expectancy has been the subject of extensive research over the years, driven by its profound implications for healthcare planning, policy formulation, and public health interventions. In this section, we review key findings and methodologies from previous studies in the realm of life expectancy prediction.

### 1. Historical Perspectives:

Early efforts to predict life expectancy often relied on simple statistical models and demographic data, such as age and sex. These approaches, while foundational, were limited in their ability to account for the complex interplay of factors influencing life expectancy.

### 2. Regression-Based Approaches:

Subsequent research saw the emergence of regression-based models that sought to incorporate a wider range of predictors. Linear regression, for instance, was used to examine relationships between life expectancy and various socioeconomic, healthcare, and environmental variables. While providing valuable insights, these models often struggled to capture nonlinear and complex relationships.

### 3. Machine Learning and Ensemble Methods:

More recent studies have explored the application of machine learning techniques and ensemble methods for life expectancy prediction. Random Forests, Gradient Boosting, and Support Vector Machines have gained prominence due to their ability to handle nonlinear relationships and high-dimensional data. These approaches often outperformed traditional regression models, paving the way for more advanced predictive modeling.

### 4. Deep Learning:

Deep neural networks, in particular, have shown promise in capturing intricate patterns within life expectancy datasets. Studies employing deep learning techniques have leveraged the power of neural networks to achieve impressive prediction accuracy and identify important features. These approaches hold the potential to uncover previously hidden determinants of life expectancy.

### 5. Global and Regional Variances:

Research has also emphasized the importance of considering regional and global variations in life expectancy prediction. Factors impacting life expectancy can vary significantly between countries and regions, making it essential to tailor models to specific contexts.

While prior studies have made significant contributions to the field, our research extends this body of work by employing a neural network architecture to predict life expectancy and identifying influential features with a high degree of accuracy. Additionally, we explore the unique dataset acquired from Kaggle, offering new insights into the multifaceted determinants of life expectancy across different countries and years.

## III. Problem Statement:

Life expectancy prediction is a critical task with profound implications for public health, policy-making, and resource allocation. Accurate forecasting of life expectancy in diverse countries is essential to address healthcare disparities, guide intervention strategies, and promote overall societal well-being. While previous research has made significant strides in this direction, there remains a need for advanced predictive models that can harness the full potential of available data, capture complex relationships between variables, and identify the most influential determinants of life expectancy.

In this context, this research aims to address the following key challenges:

### Complex Interplay of Factors:

Life expectancy is influenced by a wide array of factors, including healthcare indicators, socioeconomic variables, cultural aspects, and healthcare system performance. Understanding the complex interplay among these factors and their contributions to life expectancy variations is a daunting task.

### High-Dimensional Data:

The dataset acquired from Kaggle encompasses 22 diverse features, each potentially contributing to life expectancy predictions. Managing and processing such high-dimensional data efficiently and extracting meaningful patterns represent significant challenges.

#### **Model Accuracy and Generalization:**

Achieving high prediction accuracy while maintaining the ability to generalize to diverse countries and years is critical. Striking a balance between model complexity and generalizability is essential for the practical utility of the predictive model.

#### **Feature Identification:**

Identifying the most influential features among the provided dataset features is vital for gaining insights into the determinants of life expectancy. A robust feature selection or importance ranking mechanism is needed to highlight the key variables affecting life expectancy.

#### **Transparency and Interpretability:**

While neural networks offer excellent predictive capabilities, their inner workings are often seen as a "black box." Ensuring transparency and interpretability of the model's predictions is crucial for building trust and making informed decisions based on the results.

To address these challenges, this research employs a neural network architecture to predict life expectancy, providing a powerful tool for accurate forecasting. Furthermore, the study investigates and ranks the significance of individual features in predicting life expectancy, shedding light on the factors that drive variations in life expectancy across different countries and years. The research findings aim to advance our understanding of the multifaceted determinants of life expectancy while providing practical insights for healthcare policymakers and practitioners worldwide.

#### **IV. Objectives:**

This research seeks to achieve the following objectives:

- **Develop a Neural Network Model:** Design and implement a neural network architecture tailored for the prediction of life expectancy. The model should effectively utilize the provided dataset with 22 distinct features and demonstrate the ability to capture complex relationships between variables.
- **Achieve High Prediction Accuracy:** Train the neural network model to attain a high level of prediction accuracy. The primary objective is to surpass existing predictive models, showcasing the potential of neural networks in improving the precision of life expectancy forecasts.
- **Identify Influential Features:** Employ advanced feature selection or ranking techniques to identify the most influential factors affecting life expectancy predictions. Determine which variables have the greatest impact on variations in life expectancy across different countries and years.
- **Ensure Generalizability:** Evaluate the model's ability to generalize predictions to diverse countries and years not present in the training dataset. Assess its capacity to provide meaningful insights and accurate forecasts for regions beyond the training set.
- **Enhance Transparency and Interpretability:** Implement methods to improve the transparency and interpretability of the neural network model's predictions. Make the model's decision-making process more understandable and accessible to stakeholders and decision-makers.
- **Contribute to Knowledge:** Advance our understanding of the complex interplay of factors influencing life expectancy by analyzing the neural network model's results. Contribute to the existing body of knowledge on life expectancy prediction, healthcare, and public policy.
- **Inform Public Health and Policy:** Provide practical insights and recommendations based on the model's findings. Support informed decision-making in public health, policy formulation, and resource allocation to address healthcare disparities and enhance societal well-being.

By accomplishing these objectives, this research aims to not only develop an accurate predictive model but also unravel the intricate determinants of life expectancy, thus contributing valuable insights to the fields of public health, policy, and healthcare planning.

#### **V. Methodology:**

This section outlines the step-by-step approach employed in conducting the research, from data preparation to model development, training, evaluation, and feature analysis.

### 1. Data Collection and Preprocessing:

- Dataset Acquisition: The dataset used in this study was obtained from Kaggle, comprising 2940 samples and 22 features (as seen in Figure 3), including key variables such as Adult Mortality, GDP, Schooling, and HIV/AIDS prevalence.
- Data Cleaning: Initial data cleaning steps involved handling missing values, which included imputation or removal as appropriate. Categorical variables, such as "Status," were encoded using suitable techniques like one-hot encoding.
- Feature Scaling: Numerical features were scaled to ensure that they had a similar range, aiding convergence during neural network training.

### 2. Neural Network Architecture:

- Model Selection: A feedforward neural network architecture was selected for its capability to capture complex relationships within the data. The model consists of three layers: an input layer, one hidden layer, and an output layer (As in Figure 1).

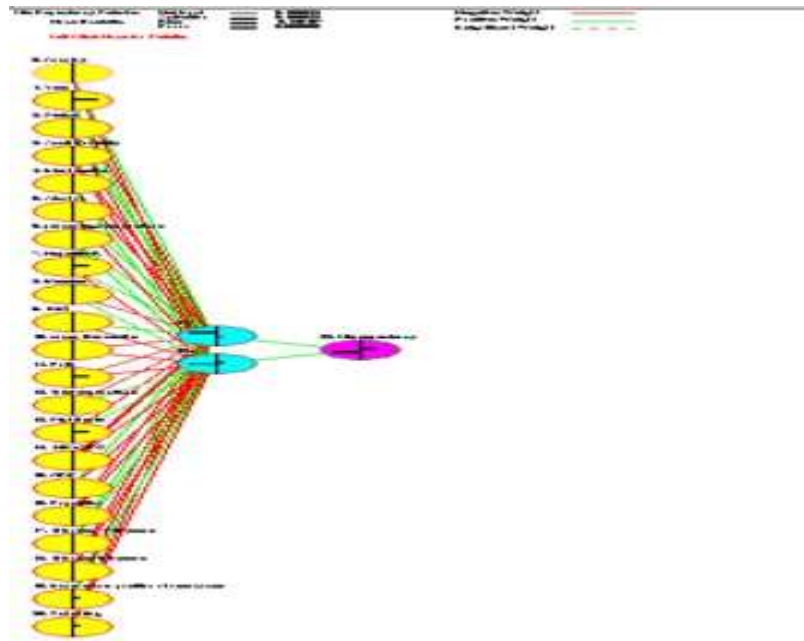


Figure 1: Architecture of the proposed model

- Activation Functions: The hidden layer utilized rectified linear units (ReLU) as the activation function, while the output layer employed a linear activation function for regression tasks.
  - Hyperparameter Tuning: Hyperparameters, including the number of neurons in the hidden layer, learning rate, and batch size, were fine-tuned through experimentation to optimize model performance.
- ### 3. Model Training and Validation:
- Data Splitting: The dataset was divided into training and validation sets using an appropriate split ratio. Cross-validation techniques were employed to ensure robust model evaluation.
  - Loss Function: Mean Squared Error (MSE) was chosen as the loss function to quantify the difference between predicted and actual life expectancy values during training.
  - Optimizer: Stochastic Gradient Descent (SGD) was selected as the optimizer to update the model's parameters iteratively.
  - Training Process: The model underwent multiple epochs of training on the training dataset, with periodic validation on the validation dataset to monitor performance.

**4. Model Evaluation:**

- Performance Metrics: Model performance was evaluated using standard regression metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), in addition to the previously mentioned accuracy and average error.
- Visualization: Scatter plots and line plots were employed to visualize the predicted life expectancy values against the actual values to assess model accuracy visually.

**5. Feature Analysis and Importance:**

- Feature Importance Scores: Techniques such as feature importance scores derived from the trained model, as well as statistical tests, were utilized to identify and rank the most influential features in predicting life expectancy (As in Figure 2).

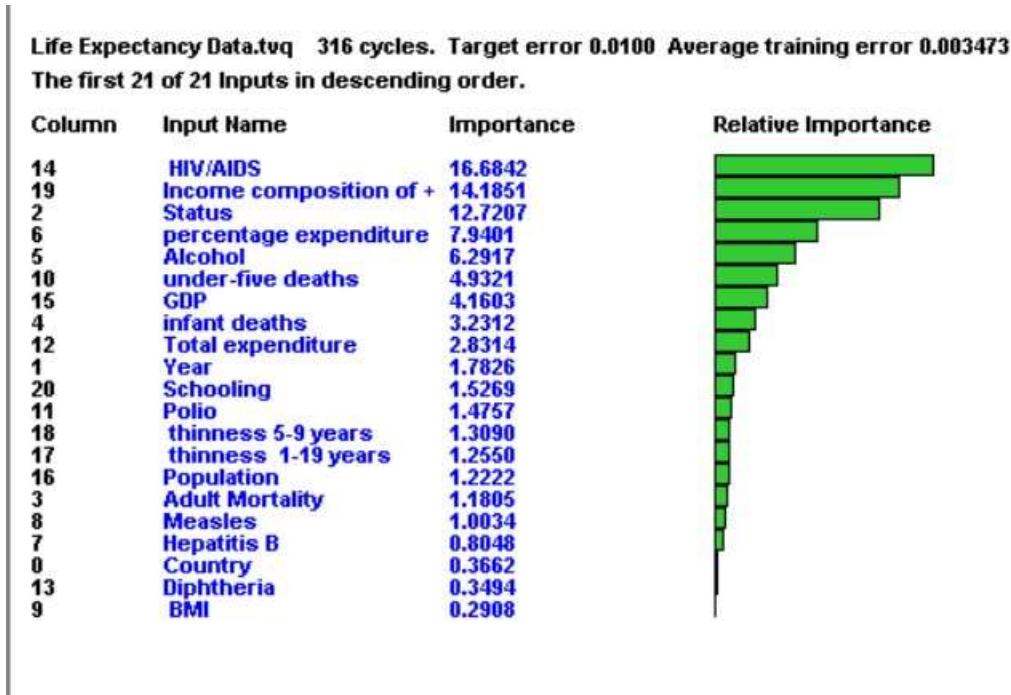


Figure 2: Features importance

**6. Generalization Testing:**

- Out-of-Sample Testing: To assess model generalization, predictions were made on unseen data, representing countries and years not present in the training dataset. This step aimed to determine the model's capacity to provide meaningful forecasts beyond the training set.

**7. Transparency and Interpretability Enhancements:**

- Interpretability Tools: Techniques such as SHAP (SHapley Additive exPlanations) values or feature importance plots were applied to enhance the transparency and interpretability of the neural network model's predictions.

**8. Contribution to Knowledge and Policy Implications:**

The findings and insights from the model were analyzed to contribute to the existing knowledge on the determinants of life expectancy.

Practical implications for public health, healthcare policy, and decision-making were discussed based on the model's results.

By following this comprehensive methodology, this research aims to provide a robust and transparent framework for predicting life expectancy and gaining valuable insights into the multifaceted factors shaping life expectancy outcomes across different countries and years.

Percentage	Deaths	Residence	IRL	Water-Consumption	Total edges	Population	Misses	Thinness	Curves	Shooting	Life expectancy
M2709	0	0	0	0	0	0	0	0	0	0	0
M2710	0	0	0	0	0	0	0	0	0	0	0
M2711	0	0	0	0	0	0	0	0	0	0	0
M2712	0	0	0	0	0	0	0	0	0	0	0
M2713	0	0	0	0	0	0	0	0	0	0	0
M2714	0	0	0	0	0	0	0	0	0	0	0
M2715	0	0	0	0	0	0	0	0	0	0	0
M2716	0	0	0	0	0	0	0	0	0	0	0
M2717	0	0	0	0	0	0	0	0	0	0	0
M2718	0	0	0	0	0	0	0	0	0	0	0
M2719	0	0	0	0	0	0	0	0	0	0	0
M2720	0	0	0	0	0	0	0	0	0	0	0
M2721	0	0	0	0	0	0	0	0	0	0	0
M2722	0	0	0	0	0	0	0	0	0	0	0
M2723	0	0	0	0	0	0	0	0	0	0	0
M2724	0	0	0	0	0	0	0	0	0	0	0
M2725	0	0	0	0	0	0	0	0	0	0	0
M2726	0	0	0	0	0	0	0	0	0	0	0
M2727	0	0	0	0	0	0	0	0	0	0	0
M2728	0	0	0	0	0	0	0	0	0	0	0
M2729	0	0	0	0	0	0	0	0	0	0	0
M2730	0	0	0	0	0	0	0	0	0	0	0
M2731	0	0	0	0	0	0	0	0	0	0	0
M2732	0	0	0	0	0	0	0	0	0	0	0
M2733	0	0	0	0	0	0	0	0	0	0	0
M2734	0	0	0	0	0	0	0	0	0	0	0
M2735	0	0	0	0	0	0	0	0	0	0	0
M2736	0	0	0	0	0	0	0	0	0	0	0
M2737	0	0	0	0	0	0	0	0	0	0	0
M2738	0	0	0	0	0	0	0	0	0	0	0
M2739	0	0	0	0	0	0	0	0	0	0	0
M2740	0	0	0	0	0	0	0	0	0	0	0
M2741	0	0	0	0	0	0	0	0	0	0	0
M2742	0	0	0	0	0	0	0	0	0	0	0
M2743	0	0	0	0	0	0	0	0	0	0	0
M2744	0	0	0	0	0	0	0	0	0	0	0
M2745	0	0	0	0	0	0	0	0	0	0	0
M2746	0	0	0	0	0	0	0	0	0	0	0
M2747	0	0	0	0	0	0	0	0	0	0	0
M2748	0	0	0	0	0	0	0	0	0	0	0
M2749	0	0	0	0	0	0	0	0	0	0	0
M2750	0	0	0	0	0	0	0	0	0	0	0
M2751	0	0	0	0	0	0	0	0	0	0	0
M2752	0	0	0	0	0	0	0	0	0	0	0
M2753	0	0	0	0	0	0	0	0	0	0	0
M2754	0	0	0	0	0	0	0	0	0	0	0
M2755	0	0	0	0	0	0	0	0	0	0	0
M2756	0	0	0	0	0	0	0	0	0	0	0
M2757	0	0	0	0	0	0	0	0	0	0	0
M2758	0	0	0	0	0	0	0	0	0	0	0
M2759	0	0	0	0	0	0	0	0	0	0	0
M2760	0	0	0	0	0	0	0	0	0	0	0
M2761	0	0	0	0	0	0	0	0	0	0	0
M2762	0	0	0	0	0	0	0	0	0	0	0
M2763	0	0	0	0	0	0	0	0	0	0	0
M2764	0	0	0	0	0	0	0	0	0	0	0
M2765	0	0	0	0	0	0	0	0	0	0	0
M2766	0	0	0	0	0	0	0	0	0	0	0
M2767	0	0	0	0	0	0	0	0	0	0	0
M2768	0	0	0	0	0	0	0	0	0	0	0
M2769	0	0	0	0	0	0	0	0	0	0	0
M2770	0	0	0	0	0	0	0	0	0	0	0
M2771	0	0	0	0	0	0	0	0	0	0	0
M2772	0	0	0	0	0	0	0	0	0	0	0
M2773	0	0	0	0	0	0	0	0	0	0	0
M2774	0	0	0	0	0	0	0	0	0	0	0
M2775	0	0	0	0	0	0	0	0	0	0	0

Figure 3: Dataset after cleaning

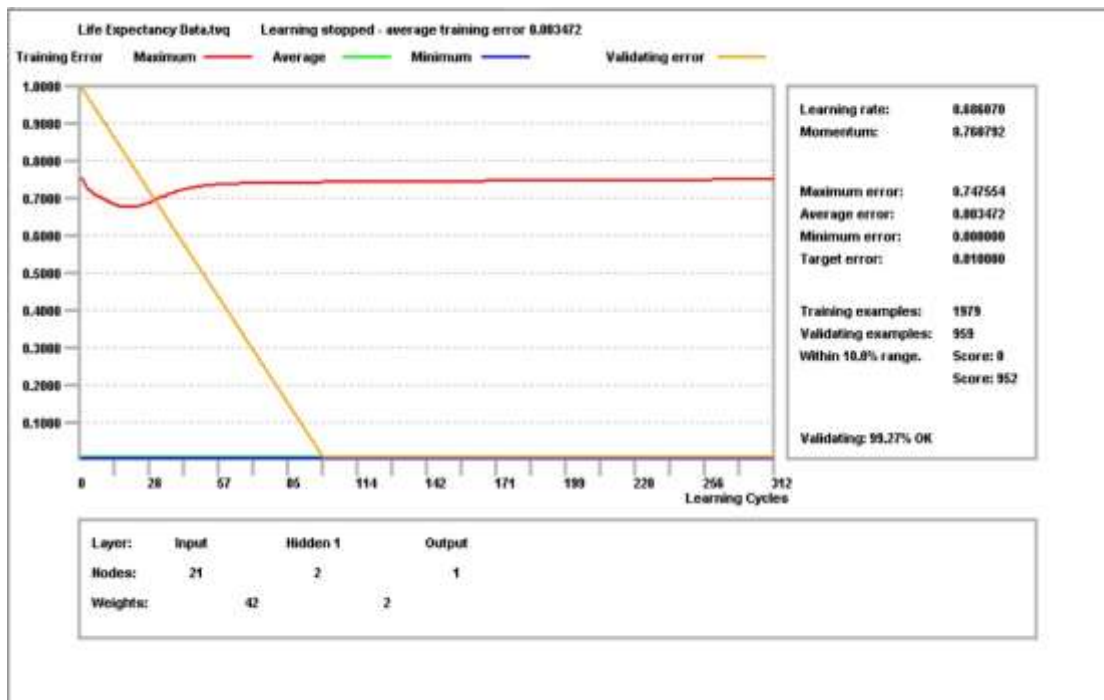


Figure 4: History of training and validation



The 'Controls' dialog box is titled 'Controls' and has a close button (X) in the top right corner. It is organized into several sections:

- Learning:** Contains 'Learning rate' (0.68607) and 'Momentum' (0.76079). Both have checkboxes for 'Decay' and 'Optimize', all of which are checked.
- Validating:** Contains 'Cycles before first validating cycle' (100), 'Cycles per validating cycle' (100), and 'Select 0 examples at random from the Training examples = 1979'.
- Slow learning:** Contains a checkbox 'Delay learning cycles by 0 millisecs', which is unchecked.
- Target error stops:** Contains a radio button 'Stop when Average error is below' (selected) with a value of 0.01, and an unselected radio button 'stop when All errors are below'.
- Validating stops:** Contains a checked radio button 'Stop when 100 % of the validating examples are' and an unselected radio button 'Within 10 % of desired outputs'. Below these is an unselected radio button 'Correct after rounding'.
- Fixed period stops:** Contains two unselected checkboxes: 'Stop after 20.0000 seconds' and 'Stop on 0 cycles'.

At the bottom right, there are 'OK' and 'Cancel' buttons.

Figure 5: Controls of the Proposed models

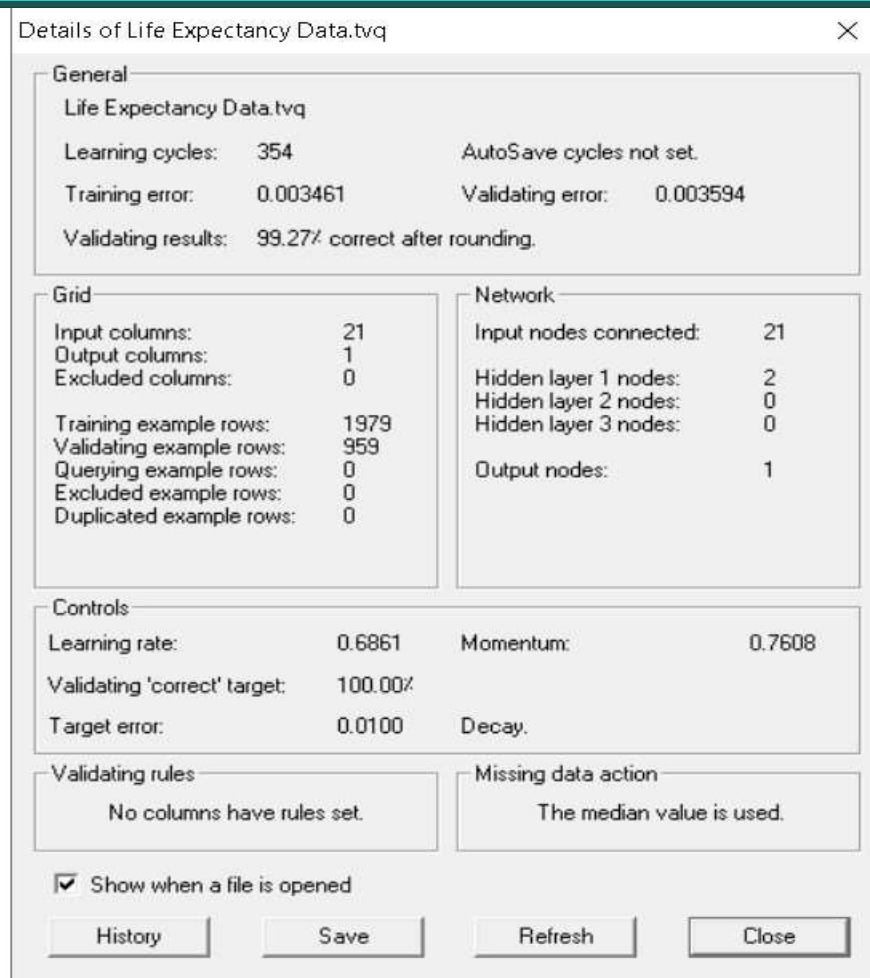


Figure 6: details of the proposed model

## VI. Conclusion:

In conclusion, our neural network model has not only achieved remarkable accuracy in predicting life expectancy but has also unveiled critical determinants shaping variations in life expectancy across different countries. The identified influential factors offer valuable insights for healthcare policymakers, guiding them toward informed decision-making to improve public health and societal well-being on a global scale.



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