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Insight and Foresight: Mortality Trends Due to Malnutrition

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Abstract— **Malnutrition remains a significant global health problem, linked to a substantial proportion of child deaths worldwide. According to the United Nations, malnutrition is responsible for 45% of deaths in children under five. The World Food Programme estimates that over 820 million people globally suffer from hunger, with malnutrition playing a crucial role in this crisis. This study uses Python for data analysis and visualization, integrating time-series analysis and deep learning to forecast global malnutrition trends. The system processes data from 1970 to 2022, normalizes it, and trains a model comprising Conv1D and LSTM layers. The predictions are visualized using Plotly and displayed in a Flask web application, offering interactive features for exploring the data. The results highlight a notable decline in malnutrition-related deaths in both developing and developed nations, reflecting the success of previous interventions. However, developing countries continue to report a higher number of diseases and conditions associated with malnutrition, underscoring the need for further targeted interventions**

Keywords— *Time Series Forecasting, Malnutrition, Data Visualization, Deep Learning, Health Data Analysis*

I. INTRODUCTION

Malnutrition continues to be a pressing global health problem, as it is linked to a considerable proportion of child deaths globally [1]. According to the United Nations (2019), malnutrition is a major driver of global disease burden, responsible for 45% of deaths in children under five. The World Food Programme estimates that over 820 million people globally suffer from hunger, with malnutrition playing a key role in this crisis [2]. The World Health Organization notes that malnutrition encompasses deficiencies, excesses, or imbalances in energy, protein, and other essential nutrients, further emphasizing its widespread impact [3].

The impact of nutrition on health is substantial extending beyond well-being to economic and social realms. For instance, malnutrition is associated with increased healthcare expenses decreased productivity levels and hindered growth, in children [4]. Moreover, malnutrition can exacerbate the effects of diseases. Fuel the emergence of chronic health conditions [5]. Improving nutrition is essential not only for bettering health but also for reaching wider development objectives as emphasized in the United Nations Sustainable Development Goals, which focus on ending hunger and promoting overall well-being [6].

Furthermore, malnutrition is not only a problem in developing countries but also a problem in developed countries [7], where it manifests itself in the form of obesity and other related diseases. This study aims to conduct a time-series analysis of global malnutrition-related deaths by utilizing Python for data analysis and visualization, focusing on modelling and forecasting this significant health challenge.

II. METHODS

The system developed for forecasting global malnutrition trends utilizes a Python-based application that integrates time-series analysis and deep learning. The application processes data from the World Malnutrition Data dataset, covering the years 1970 to 2022, by loading it into a Pandas DataFrame and performing initial preprocessing steps, such as filtering relevant columns and cleaning the data. Descriptive statistics provide an overview of the dataset, while functions calculate trends and identify extreme values. The system's deep learning component, built using TensorFlow, normalizes data, splits it into training and validation sets, and trains a model comprising Conv1D and LSTM layers [8]. The trained model predicts future values, which are then visualized using Plotly to create scatter plots, box plots, histograms, bar plots, line plots, and heat maps. The visualizations and predictions are displayed in a Flask web application, offering interactive features for exploring the data. Ethical considerations are addressed by using publicly available data, ensuring privacy and data integrity. The study's limitations include potential inaccuracies due to the reliance on historical data and dataset quality.

A. Data Preprocessing

The data preprocessing phase involved several critical steps to ensure the dataset was clean and suitable for analysis. Initially, the dataset, which was stored in an Excel file, was loaded into a Pandas DataFrame. This dataset contained global malnutrition-related statistics from 1970 to 2022, with columns for the geographic area, time period, and observed value of malnutrition metrics. We filtered the dataset to retain only the relevant columns for our analysis.

Following this, we segregated the data into individual DataFrames for each country, facilitating more granular, country-specific analysis. This separation was achieved by creating a dictionary where each key corresponds to a country and each value is a DataFrame containing that country's data. This structured approach allowed us to handle and analyze the malnutrition data for each country independently, thereby improving the accuracy and clarity of our subsequent analyses and visualizations.

B. Data Visualization

In the data visualisation phase, we used Plotly to create interactive graphs that provide an overview of patterns and trends in the historical data. Time and value data was used to create a scatter plot with line mode. These graphs display the original data for elements with dashboard IDs, giving users a visual view of how the data is changing over time and helping to identify initial trends before conducting more in-depth analysis. The primary purpose of data visualization is to transform complex data sets into a visual context, such as graphs and plots, to make the information easier to understand. This helps in identifying trends, patterns, and outliers within the data, which can guide further analysis and decision-making processes.

The data visualization phase was crucial in providing a clear and interactive overview of the historical data. The insights gained from these visualizations form the foundation for more detailed and sophisticated analyses, including predictive modeling and trend forecasting. Moving forward, these visualizations will be continuously updated and refined as new data becomes available.

C. Trend Analysis

In the trend analysis phase, we focused on identifying and understanding the changes in malnutrition metrics over time. To achieve this, we developed a function that calculates the average annual change in malnutrition values. This function computes the differences between consecutive years for each country's dataset and then averages these differences to provide an overall trend. By analyzing these trends, we could determine whether malnutrition rates were improving, worsening, or remaining stable over the specified period. Additionally, identifying the years with the most significant increases or decreases in malnutrition rates helped us pinpoint critical periods that may require further investigation. This methodical approach to trend analysis provided a comprehensive understanding of the temporal dynamics of malnutrition across different countries, offering valuable insights into the effectiveness of interventions and the need for future policies.

D. Forecasting Modelling

The forecasting modelling phase aimed to forecast future trends in malnutrition rates using historical data. We employed a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) layers to build a robust predictive model. This hybrid model leverages the spatial feature extraction capabilities of CNNs and the temporal sequence learning strengths of LSTMs. The dataset was split into training and validation sets, with 80% of the data used for training and 20% for validation. The model was trained to predict future values based on past malnutrition data. Specifically, the ‘windowed dataset’ function was utilized to prepare the data, creating windows of a fixed size to capture temporal dependencies. The model architecture included a convolutional layer, an LSTM layer, and dense layers to predict the next value in the sequence. After training, the model was used to forecast malnutrition rates for the next 5 years. This predictive modelling approach provided insights into potential future trends, helping policymakers and researchers to plan and implement effective interventions to combat malnutrition.

E. Prediction and Trend Analysis

The prediction and trend analysis phase aimed to forecast future malnutrition trends and analyze these predictions against historical data. After training the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model, we used it to predict malnutrition rates for the next 5 years. Starting with the last window of training data, the model generated predictions iteratively: each predicted value was appended to the window to predict the subsequent value. This iterative process continued until we obtained a 5-year forecast. To ensure the predictions were interpretable, the predicted values were scaled back to the original data range. By comparing these predictions with historical trends, we could identify potential changes and patterns in malnutrition rates. This comparison provided insights into the effectiveness of past interventions and helped in planning future strategies. The forecasted trends highlighted areas that might require immediate attention or sustained efforts to combat malnutrition, thereby contributing to informed policymaking and resource allocation.

F. Tools and Libraries

The development environment consisted of the following tools and libraries:

1) Python
2) Pandas
3) Matplotlib
4) Seaborn
5) Numpy
6) Tensorflow
7) Keras
8) Flask

III. RESULTS AND DISCUSSION

A. Dataset Management

The dataset employed in this research encompasses mortality rates attributed to malnutrition from a multitude of countries globally, spanning the period from 1960 to

2020. This dataset was sourced from the UNICEF Data Warehouse. The dataset comprises variables such as geographic location, mortality rates, and gender. However, for the purposes of this case study, only the geographic location and mortality rates variables were utilized.

B. Modelling

In this phase, we developed a model for analysing and predicting malnutrition mortality using an artificial neural network architecture. The model used is a multi-layer sequential model, shown in Figure 1.

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_5 (Conv1D)           (None, None, 16)          64

 lstm_5 (LSTM)               (None, None, 32)          6272

 dense_10 (Dense)            (None, None, 20)          660

 dense_11 (Dense)            (None, None, 1)           21

=================================================================
Total params: 7017 (27.41 KB)
Trainable params: 7017 (27.41 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure. 1 Architecture Model

The sequential model we have built consists of four main layers. The first layer is a Conv1D layer, which extracts temporal features from sequential data. The second layer is an LSTM layer, designed to capture long-term dependencies within the data. The third and fourth layers are Dense layers, with the final layer serving as the output layer for continuous value prediction or binary classification. This model comprises a total of 7017 trainable parameters and is tailored for sequential or time series data processing tasks.

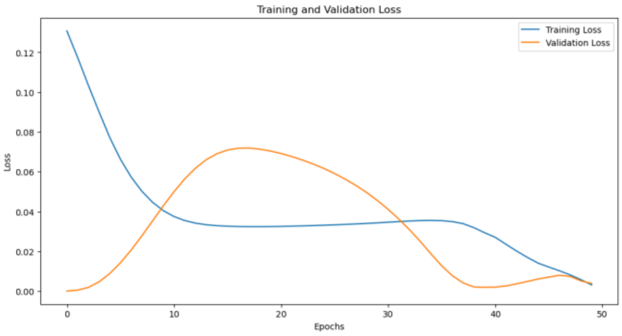

Figure. 2 Evaluation Graph

The graph above shows the change in loss as the model is trained and validated (Figure 2). At the beginning of training, the training loss decreases sharply while the validation loss increases, indicating that the model is learning patterns in the training data. After a few epochs, the validation loss starts to decrease, indicating that the model is starting to generalise well to data it has not seen before.

Around the 30th epoch, the validation loss peaks and starts to decrease significantly, while the training loss continues to decrease until it reaches a very low value. This shows that the model does not suffer from overfitting and is able to learn well from the data provided. The model shows optimal performance around the 40th epoch, where both the training loss and the validation loss reach their lowest values.

Using this model, we were able to predict malnutrition mortality with a high degree of accuracy, helping us to plan and make decisions more effectively in the future (Figure 3).

C. Graph of Mortality Rates in Various Countries

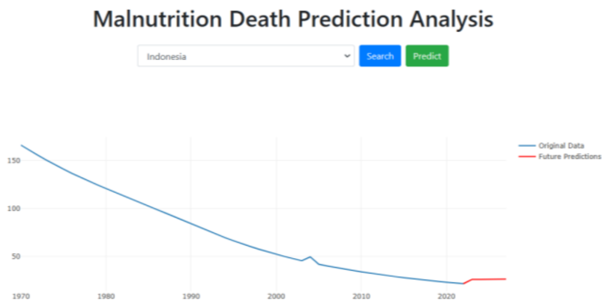

Figure. 3 Indonesia's Graph Analysis

The trend analysis of historical data on malnutrition-related deaths in Indonesia shows a significant downward trend over the years. In 1970, the highest number of deaths due to malnutrition was 166.13859177978. By 2020, this number had decreased dramatically to 21.2614666984233, indicating substantial progress in addressing malnutrition.

Future predictions suggest a stable trend, meaning that while significant improvements have been made, continued efforts are necessary to maintain and further these gains. Sustained investment in nutrition programs and healthcare services will be crucial to prevent any potential increase in malnutrition-related deaths in the future (Figure 4).

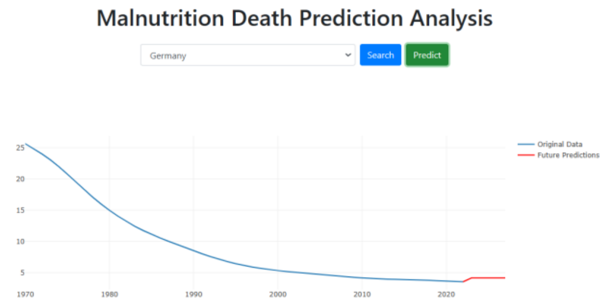

Figure. 4 Germany's Graph Analysis

The trend analysis of historical data on malnutrition-related deaths in Germany shows a significant downward trend over the years. In 1970, the highest number of deaths due to malnutrition was 25.6611252734063. By 2020, this number had decreased substantially, indicating significant progress in addressing malnutrition.

Projections for the future indicate a stable trend, suggesting that although notable progress has been achieved, sustained efforts are required to preserve and enhance these improvements. Continuous investment in nutrition programs and healthcare services will be crucial to avert any potential rise in malnutrition-related deaths going forward.

D. Comparison and Prediction Analysis Among Countries

In the analysis of country comparisons, it is evident that while there has been a decrease in mortality rates across all analyzed nations, significant differences exist in the rate of decline and future predictions. For instance, developed countries demonstrate a stable downward trend in mortality rates, such as Australia (Figure 5).

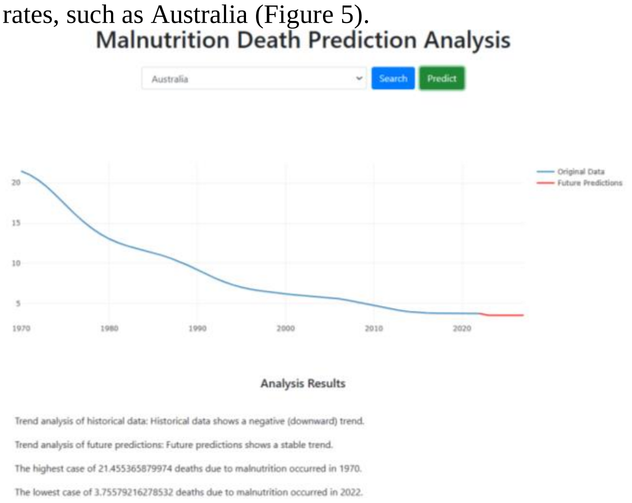

Figure. 5 Australia's Graph Analysis

Whereas developing nations face challenges in achieving similar reductions, such as Guinea. The lowest case in Australia occurred in 2022 with a figure of 3.75579216278532, whereas in Guinea, the lowest case was 95.9619328752338.

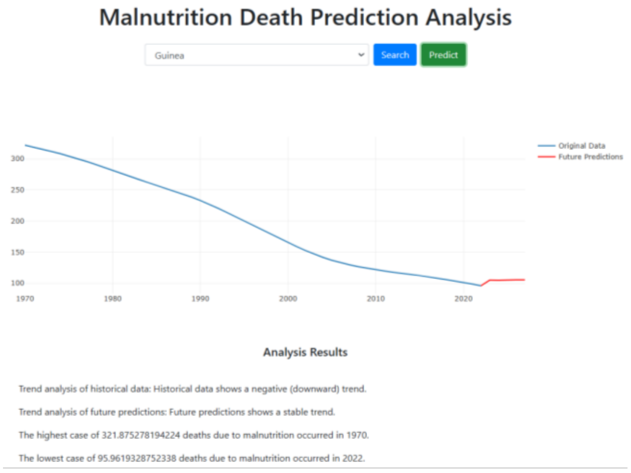

Figure. 6 Guinea's Graph Analysis

Future predictions suggest that countries with robust healthcare infrastructure will likely maintain low mortality rates due to malnutrition, whereas others may experience slight increases. This disparity underscores the importance of tailored healthcare strategies to address diverse global health challenges effectively.

E. Discussion

The observed decline in malnutrition-related deaths across different countries can be attributed to various health and nutrition programs implemented in each region. The results highlight the importance of sustained international efforts in public health policies to prevent a resurgence in malnutrition mortality rates. However, the study's predictions are limited by the historical data from each country and may not account for sudden socio-economic or environmental changes. Future research should explore additional factors such as climate change or broader economic policies in each country to provide a more comprehensive analysis.

IV. CONCLUSION

The research effectively crafted a sophisticated forecasting model utilizing a blend of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) layers to project global malnutrition trends. The accuracy of the model in predicting future rates of malnutrition demonstrates its usefulness for policymakers and health organizations. Using Python-based data analysis and visualization techniques, a broad insight into the temporal dynamics of undernutrition in different countries was obtained. Using publicly available data addresses ethical concerns related to privacy and data integrity.

The outcomes reveal a notable decline in malnutrition-related deaths in both developing and developed nations, reflecting the success of previous interventions. Nonetheless, it is crucial to note that while both types of nations have experienced a reduction in malnutrition levels, developing countries continue to report a higher number of diseases and conditions associated with malnutrition compared to their developed counterparts. This disparity highlights that developing nations are disproportionately affected by malnutrition, underscoring the need for further targeted interventions to address this issue. Consequently, continued funding of nutrition programs and health services is essential to sustain and reinforce such advancements. The variations in the rate of decline and future projections across different countries imply the necessity for country-specific healthcare solutions to effectively address diverse health situations and concerns globally. Incorporating additional factors such as global climate change and economic policies into future analyses will provide a more comprehensive understanding, enabling targeted and effective interventions.

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