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USING ARTIFICIAL INTELLIGENCE TOOLS TO PREDICT AND ALLEVIATE POVERTY*

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Abstract. This paper presents a thorough time series forecasting model intended to project future performance with respect to Sustainable Development Goal 1 (SDG 1) and the corresponding poverty index scores for the years 2024–2030, with a particular emphasis on the United States, Saudi Arabia, China, Egypt, and Sweden. A one-dimensional Convolutional Neural Network (1D-CNN) is used in the model to examine and extract patterns from historical socio-economic data from 2000 to 2022. The algorithm uses deep learning techniques to efficiently extract temporal correlations from the data, allowing for accurate predictions of each country's progress towards ending poverty and raising living standards. Because it can effectively handle time series data and find connections and patterns in earlier observations to guide future advancements in poverty alleviation tactics, the 1D-CNN architecture was chosen. The model was trained and validated using historical data to ensure predictions for the following years were based on real dynamics. To reflect the viability of reaching SDG 1 targets, forecasts were also limited to a realistic range of 0 to 100. The findings show that the model can correctly forecast shifts in poverty levels, which is consistent with expected worldwide patterns. These projections offer insightful information for international organisations, stakeholders, and policymakers involved in sustainability programs. By giving decision-makers the insight they need to deploy resources and carry out successful interventions effectively, the strategy speeds up the process of reaching SDG 1.

Keywords: Sustainable Development Goals (SDGs); one-dimensional Convolutional Neural Network; SDGs Index Score; deep learning, AI

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1. Introduction

All United Nations member nations endorsed the 2030 Agenda for Sustainable Development in 2015, laying forth a shared vision for a sustainable future that includes social equality, economic prosperity, and environmental protection (Naciones Unidas, 2022). It lays out the 17 Sustainable Development Goals (SDGs), each of which aims to address one of the most critical issues facing humanity at the moment: ending poverty, enhancing health and education, decreasing inequality, accelerating economic growth, addressing climate change; and advancing environmental preservation as shown in Figure 1. A worldwide framework for attaining sustainable development that guarantees that "no one is left behind" is provided by the Sustainable Development Goals (SDGs) (Sachs et al., 2022). The Sustainable Development Goals (SDGs) encompass a comprehensive approach to sustainability in addition to concentrating on certain theme areas like poverty reduction (SDG 1), education quality (SDG 4), and climate action (SDG 13). For instance, achieving one goal frequently influences achieving another, demonstrating how interrelated the goals are. Goals like life below water (SDG 14) and life on land (SDG 15) are directly impacted by efforts to tackle climate change (SDG 13). Similarly, gender equality (SDG 5) is crucial for promoting health, economic growth, and social justice.

The SDGs remain highly challenging to achieve by 2030 despite the worldwide desire. The world is not on track to reach many of the goals, according to the UN Sustainable Development Report 2022. In other areas, progress has been reversed as a result of global crises like the COVID-19 pandemic, economic downturns, and geopolitical tensions (Stafford-Smith et al., 20217; Barbier & Burgess, 2020; Vyas-Doorgapersad, 2024). Consequently, there is an increasing need for data-driven insights to monitor and predict progress.

Figure 1. Sustainable Development Goals (SDGs).

Accurate monitoring is crucial to give policymakers the information they need to modify plans, distribute funds wisely, and pinpoint regions that most require intervention (Fukuda-Parr & McNeill, 2019). Since every country has a unique set of political, economic, and environmental circumstances, tracking progress towards the SDGs is much more difficult (OECD, 2017). These differences imply that while certain countries might be making steady progress towards their goals, others might lag behind or face significant obstacles. For example, low-income nations frequently have challenges related to inadequate data infrastructure and resources for tracking their development, which makes it challenging to quantify SDG achievement precisely. This discrepancy

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highlights how crucial it is to use cutting-edge, data-driven strategies, including machine learning and predictive modelling, to more accurately assess and forecast SDG trends at the national and international levels (Elias et al., 2024). These methods can assist in navigating the complexity of the SDGs' interrelated nature and offer insights essential for well-informed, strategic decision-making by combining historical data and advanced algorithms.

This paper aims to use 1D Convolutional Neural Networks (1D-CNN) to create a sophisticated predictive model for predicting the SDG 1 (No Poverty) score. This study offers a strategic perspective on poverty reduction initiatives in various situations by forecasting the individual poverty scores for SDG 1 in China, Egypt, Saudi Arabia, Sweden, and the US. While China's large-scale implementation tactics in clean energy and poverty reduction offer insights from a significant developing economy (Yu et al., 2020; Lenkaitis, 2022).

Egypt's economic reforms and investments in renewable energy offer essential insights into advancing the SDGs in a rapidly rising area (Hussein & Pollock, 2019; El Baradei, 2020; Eissa, 2020). Saudi Arabia's Vision 2030, which emphasises infrastructure, economic diversification, and sustainable cities, aligns with several SDGs (AlArjani et al., 2021; Al-Mwzaiji & Muhammad, 2023). Sweden is a leader in sustainability. Thus, it provides a standard when comparing performance (Eliasson & Gr¨onlund, 2023; Palm, 2023). The USA’s leadership in innovation, sustainable cities, and climate action reflects a developed-world approach (Lenkaitis, 2022).

These projections cover the years 2024–2030. 1D Convolutional Neural Networks (1D-CNNs) are especially well-suited for this study due to their efficacy in analysing temporal data. 1D-CNNs, in contrast to conventional convolutional networks made for image processing, are specifically made to handle sequential data, such time series. Historical socio-economic data from 2000 to 2022 serves as the basis for the model training dataset in this study. This historical data will teach the 1D-CNN to spot patterns and trends, which will then help it predict future SDG 1 results.

The structure of this paper is as follows: We begin with a review of related work to provide context and background. Following this, we describe the dataset and methodology employed in our study. Next, we present a detailed implementation of the 1D-CNN model, covering its design and training process. Finally, we showcase the results, including the model's performance metrics, such as training and validation loss, and provide the predicted SDG scores for 2024 to 2030 years.

2. Related Work

Predicting Sustainable Development Goal (SDG) scores has been a growing area of research in recent times, employing various methods to find trends and project results. This research falls into a few major categories that can be generally classified. Conventional regression models have been used to find correlations between SDG scores and predictor factors, providing information on how specific SDG targets might advance. For instance, forecasting future SDG results using linear regression models, which use historical data, is normal practice. Though these models offer a fundamental foundation for forecasting, they frequently need to be revised to handle the intricate, non-linear correlations present in SDG data. According to (Singh et al., 2024), linear models cannot adequately represent the complex interdependencies between various SDG objectives and factors and are essential for precise forecasting. The shortcomings of these conventional methods are emphasised by (Bennich et al., 2023), who point out that they cannot simulate the intricate relationships and temporal dynamics present in SDG data. This has prompted researchers to investigate more advanced techniques. Time series analytic methods have been used to simulate SDG score patterns over time, such as ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA). These algorithms work very well for finding patterns and seasonal differences in SDG datasets. Li et al. (2023), for example, used these methods to predict SDG scores in different environmental settings, indicating how effective they are in capturing time-dependent aspects. Nevertheless, ARIMA and related models have several drawbacks, such as the potential to oversimplify the relationships between various SDG targets, particularly when handling numerous objectives and intricate interdependencies (Ramadan, 2024).

Machine learning techniques have surfaced as a more adaptable and potent tool for SDG prediction in response to these difficulties. Large datasets have been managed, and non-linear interactions between SDG variables have been modelled using techniques like Random Forests and Gradient Boosting Machines. Compared to standard statistical models, these ensemble approaches produce more accurate and robust forecasts because they can handle complicated interactions between predictor variables (Kumar et al., 2023). Even so, there is still a chance that machine learning models will struggle to identify temporal connections and produce findings that make sense. According to Spathis and Kawsar (2024) tokenising and encoding temporal data for machine learning models has particular difficulties that frequently result in decreased interpretability and prediction accuracy.

Despite recent breakthroughs, many currently used models need to be revised to fully represent the temporal dynamics and developing patterns found in SDG data (Selin et al., 2023). More efficient models for the analysis of sequential and time-dependent connections are required. Moreover, research frequently concentrates on specific SDGs or aggregate indices, possibly needing more all-encompassing strategies that address several objectives simultaneously (Huffman et al., 2023). Furthermore, even though predicted accuracy using machine learning models has increased, interpretability and accuracy are frequently trade-offs (Jo et al., 2023). Models that strike a balance between these factors are required for use in actual policy-making.

Furthermore, a lot of research employs data with low granularity, which reduces forecast accuracy (Wang & Chang, 2023). Prediction accuracy may be improved by including more specific and granular data. Additionally, (Taweesan et al., 2024) used machine learning to forecast diarrheal illnesses in Asia and Africa due to inadequate sanitation. Using data from 1000 households, a classification tree model (J48) was used, and it achieved 73% accuracy. Personal hygiene and sanitation techniques like open defecation are essential components.

This analysis identifies several serious flaws in the SDG 1 forecasting methods, highlighting the need for more sophisticated approaches to handle these issues successfully. The intricate temporal patterns and dynamic interconnections that affect poverty levels are complex for many current models to reflect. Although traditional methods have advantages, they can lack the sophistication needed to comprehend the complex linkages and time-dependent elements included in data pertaining to poverty. To overcome these restrictions, this study attempts to present a fresh strategy using a 1D Convolutional Neural Network (1D-CNN) model. The 1D CNN is especially well-suited for examining poverty-related sequential and time-series data because of its capacity to recognise and extract patterns over time. In contrast to traditional models, which could oversimplify or ignore the delicate dynamics of poverty trends, the 1D-CNN offers a more nuanced forecasting method by utilising its deep learning capabilities to capture and analyse complex temporal relationships.

3. Proposed Model

The process used to create the prediction model for predicting SDG 1 (No Poverty) results is described in this section. It thoroughly explains all the steps needed, including data preprocessing, the 1D Convolutional Neural Network (1D-CNN) architecture, and the training process. The technology uses sophisticated machine learning algorithms to find intricate correlations and temporal trends in data connected to poverty to produce precise forecasts.

3.1. Data Collection and Preprocessing

The Sustainable Development Goals (SDG) index, accessible on Kaggle and spans 2000–2022, provided the dataset for this investigation. This extensive dataset offers a thorough summary of national and international progress made towards the UN's 17 Sustainable Development Goals (SDGs). The dataset includes various metrics that track several social, economic, and environmental goals. SDG 1 (No Poverty) stands out among them, with particular attention paid to indicators of poverty, economic inequality, access to essential services, and social security programs. To provide a more nuanced view of the difficulties and advancements associated with accomplishing SDG 1, the study will analyse this data to identify trends and patterns that can guide efficient methods for reducing poverty. This dataset's richness and breadth allow for the use of cutting-edge machine learning methods, like the 1D Convolutional Neural Network (1D-CNN), to generate more precise forecasts of future trends in poverty.

Through computed scores, the data shows the progress made at the national and annual levels towards reaching SDG 1 (No Poverty). Specific indicators that analyse different aspects of social development and poverty reduction, such as per capita income, health outcomes, educational access, social safety nets, and environmental sustainability measures, are used to evaluate each SDG aim. These various ratings are combined to determine each nation's overall SDG Index score, which offers a thorough picture of its performance regarding the global goals for reducing poverty. Several preprocessing techniques were used to prepare the data for sequential modelling before training the 1D Convolutional Neural Network (1D-CNN) model. The collection includes SDG scores that differ by nation and goal. MinMax scaling was used to increase the model's effectiveness and guarantee consistency. All SDG scores, including the overall SDG Index, are rescaled to a range of 0 to 1 via this transformation. The method avoids features with more comprehensive numeric ranges from unduly impacting learning by normalising the values, which speeds up convergence during model training. This scaling was applied to the dataset for each nation using the MinMaxScaler function from the sklearn library. This scaling technique reduces the possibility that more significant magnitude values will obscure smaller ones in the learning process by guaranteeing that each SDG target and the SDG Index score contribute equally to the model's training. Ultimately, this preprocessing stage strengthens the predictive model's resilience, enabling a more precise evaluation of the advancement in the fight to end poverty.

3.2. Feature Selection

The data used in this study includes both individual and index scores for SDG 1 (No Poverty) and the whole dataset for all 17 SDGs. This vast dataset is a vital tool for assessing and projecting advancement towards the SDG framework of the UN, especially when tackling the pressing problems associated with poverty reduction. The dataset is arranged in a number of important columns, each of which offers crucial information for analysis:

- Country code: Each country is given a unique alphanumeric number, making cross-national comparisons and effective data management easier. It is essential for guaranteeing the integrity and consistency of data, particularly when combining various data sources.
- Country: To assist researchers in placing the data in a geographical and cultural context, this column provides a list of the names of the nations represented in the dataset. Interpreting the differences in attempts to reduce poverty and promote the SDGs requires understanding these circumstances.
- Year: Any time-series analysis must incorporate a temporal component. By indicating the year to which the data relates, this column makes it possible to analyse trends and evaluate how scores connected to poverty have changed over time. It enables scholars to assess the effects of particular policies or world events and determine the relative advantages of short- and long-term development plans.
- SDG Index Score: A country's overall achievement in accomplishing the 17 SDGs is reflected in this composite score. By offering a single indicator that captures a country's accomplishments, it makes comparisons easier both within and between nations. Finding out which nations are ahead or behind in sustainable development projects, such as reducing poverty, is made easier with the help of the SDG Index score.
- Goal 1 Score: This particular score evaluates how well a country is doing concerning SDG 1 (No Poverty). It includes a number of metrics pertaining to social safety programs, poverty levels, and access to essential services. This score's granularity makes it possible to analyse a nation's poverty reduction plans in great depth, highlighting its advantages and disadvantages in reaching SDG 1.

The need to comprehend the general and particular aspects of sustainable development motivated the adoption of SDG index scores and individual goal scores for SDG 1 (No Poverty). Researchers can rapidly evaluate overall progress in reducing poverty and spot macro trends by examining the SDG index score. On the other hand, the individual target scores offer a thorough analysis of specific metrics, emphasising the difficulties and successes related to poverty alleviation initiatives in diverse settings. Additionally, knowing how several targets interact can highlight possible trade-offs and synergies, essential for creating policies that effectively reduce poverty. For predictive modelling, the dataset's time-series component is essential. The study can find patterns and trends in past data that help predict SDG 1 results in the future. This predictive power is crucial for stakeholders hoping to foresee challenges and spot opportunities in the fight to eradicate poverty by 2030. In conclusion, this dataset is an essential tool for assessing SDG 1 progress and directing strategic and policy decision-making, eventually advancing the larger objective of sustainable development.

3.3 Model Architecture

Using sequential data, this study used a one-dimensional convolutional neural network (1D-CNN) model to predict scores for Sustainable Development Goal 1 (No Poverty). To provide insights into possible trends and support policymakers in their strategic planning for poverty alleviation, the model forecasts future SDG 1 index scores and individual target scores using historical data. As seen in Figure 2, the architecture comprises convolutional layers, pooling layers, and fully linked dense layers specially made for time-series data. Below, we thoroughly explain each model layer and its unique role in the forecasting process.

1. Input Layer: Sequences with the shape (None, 377, 1) make up the model's input. The single feature dimension represents the time-series data under analysis, and 377 denotes the number of time steps.
2. Convolutional Layers: Conv1d 6, the architecture's initial layer, is a one-dimensional convolutional layer that applies 64 filters using ReLU (Rectified Linear Unit) activation functions across the time axis. This layer's objective is to identify regional patterns or trends in the input sequence. This layer's output is shaped like (None, 375, 64), where 64 is the number of filters, and 375 is the number of time steps that the kernel size has dropped.
3. Similar in theory to the first convolutional layer, the second convolutional layer (Conv1d 7) has 128 filters, which helps the model learn higher-level and more abstract representations. This layer produces the form (None, 185, 128).
4. Pooling Layer: A MaxPooling layer comes after each convolutional layer to lower the dimensionality and computational cost. MaxPooling (max pooling1d 6 and max pooling1d 7) chooses the highest value in a sliding window to minimise the time steps. The most critical information is preserved, although the temporal resolution is reduced with this technique. For instance, the time steps are cut in half to 187 after the first pooling process and again to 92 after the second pooling procedure.
5. Flattening Layer: The flatten 3 layer flattens the resulting 2D tensor of shape (None, 92, 128) into a 1D vector with 11,776 elements following the convolution and pooling processes. This operation is required to move from the convolutional portion of the model to the fully connected dense layers.
6. Dense Layers: The dense layers learn the intricate correlations between the extracted features. There are 128 neurones in the first completely linked layer (dense 6), each with a ReLU activation function. Essential features for the prediction job are captured in a lower-dimensional space by mapping the high-dimensional flattened vector using the dense layer. A dropout layer (dropout 1) with a rate of [specify the dropout rate, e.g., 0.5] is placed after the dense layer to avoid overfitting. By randomly deactivating neurons during training, dropout regularisation lessens the model's reliance on particular neurons and improves generalisation.
7. Output Layers: The last layer, called dense 7, has 17 neurons, a linear activation function, and is fully connected. Based on the predictions, each neuron generates the anticipated score for one of the 17 targets, which corresponds to the Sustainable Development Goals (SDGs). The number of expected values for each sample is reflected in the output shape (None, 17).

80% of the dataset was used to train the model, and the remaining 20% was reserved for validation. This division makes sure the model gains knowledge from a significant amount of data while enabling efficient assessment of its performance on data that has not been seen yet. We also used batch processing, which separates the data into smaller batches or subsets. This strategy introduces stochasticity, which can aid in escaping local minima in the loss landscape and improve the model's convergence while expediting the training process. The adaptive moment (Adam) is the optimisation used in the proposed model, with the mean absolute error (MAE) loss function and root mean squared error (RMSE) as goals. Adam can adaptively learn the required parameters based on the learning process (see Table 1).

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MAE measures the average difference between the actual and predicted values, and the root square of the average of the squared differences between the actual and predicted values is known as RMSE. These can be stated as follows:

$$MAE = \frac{\sum_{j=1}^{n} |y_j - x_j|}{n} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} (y_j - x_j)^2}{n}} \tag{2}$$

where n is the total number of data points that were recorded, x_j is the expected value, and y_j is the actual value.

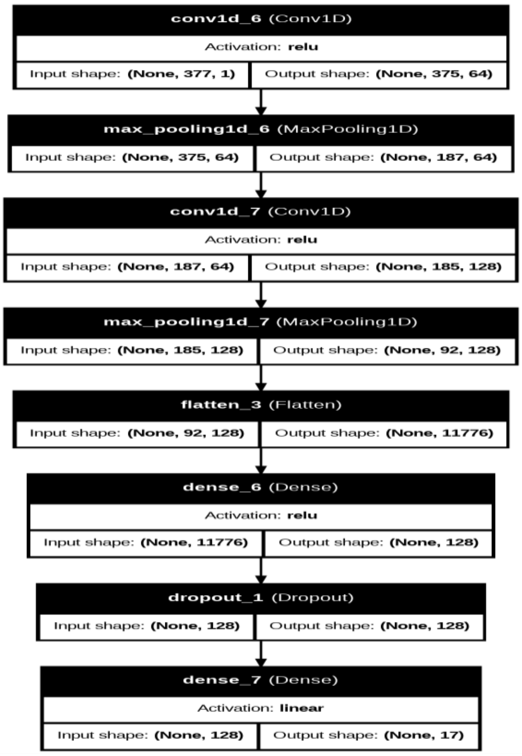

Figure 2. Proposed deep learning model

The next part discusses the experiments that were carried out to create, verify, and test the suggested model. We used 200 epochs for the training phase, which is sufficient to allow the model to identify complex patterns in the data while reducing the possibility of overfitting. The training dataset is completely traversed throughout each epoch, enabling the model weights to be changed to minimise the loss function. To ensure the model maintained its capacity for generalisation, which eventually improved its predicted accuracy on unknown data, we kept a careful eye on both training and validation losses. Using historical data from the previous three years as the time step, the model was specifically created to anticipate SDG 1 scores for the years from 2024 to 2030. The UN's 2030 timeframe for accomplishing the Sustainable Development Goals is in accordance with this anticipated horizon. The model may reflect current trends and oscillations in efforts to reduce poverty using a three-year time step, giving the projections pertinent context. Using data from the preceding three years, the system can identify patterns and shifts in SDG 1 scores that will likely affect future results.

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Table 1. 1D-CNN Model Parameters for SDG Forecasting.

Parameter	Value
Time Step	3
Batch Size	50
Epochs 200	200
Learning rate	0.001
Dropout rate	0.5
Filters (Layer 1)	64
Filters (Layer 2)	128
Kernel Size	1
Pooling Size	2
Validation Split	0.2
Min-Max Scaling Range	(-1, 1)
Optimizer	Adam
Loss Function	Mean Squared Error
Metrics	Mean Absolute Error
Training-Testing Split	80-20
Prediction Years	2024-2030

Focusing policy interventions and resource allocation on areas where poverty alleviation is falling behind enables stakeholders to make well-informed decisions based on predicted trends. Additionally, the model's output can assess how well-suited current plans and programs are to accomplishing SDG 1, which will ultimately result in more targeted and significant attempts to reduce poverty sustainably.

4. Results and Discussion

The results of the one-dimensional Convolutional Neural Network (1D CNN) model that was used to predict future SDG 1 scores are shown in this section. Training and validation datasets are used to assess the model's performance, focusing on how well it can generalise and forecast poverty reduction outcomes for 2024–2030. We review the model's main findings, evaluate how these projections might affect upcoming sustainable development projects, and contrast the expected SDG 1 scores with past patterns. The results are placed in the context of real-world uses, emphasising how the model's predictions might guide strategic planning and policy choices in the battle against poverty. Furthermore, we display the association coefficients between SDG 1 scores and other pertinent metrics in a correlation matrix. As seen in Figure 3, a correlation coefficient measures the degree and direction of a linear link between two variables. SDG 1 scores have strong positive correlations with a number of other SDGs, according to the correlation matrix, highlighting the connection between efforts to reduce poverty and more general development objectives. For example, a strong correlation of 0.84 is seen between SDG 1 (No Poverty) and SDG 4 (Quality Education), indicating that countries that successfully reduce poverty are also likely to improve the quality of education. Policymakers can use the correlation matrix's insights to create plans that concurrently target several SDGs. Given their close ties, a nation concentrating on accomplishing SDG 1 should think about directing resources towards SDG 4. By guiding resource allocation to optimise benefits across several development goals, policymakers can also find possible trade-offs and synergies by understanding these relationships. Additionally, this matrix shows interesting associations that need more research to understand the underlying causes of these correlations.

The 1D-CNN model's training and validation loss curves, shown in Figure 4, are essential for assessing the model's functionality and spotting possible problems like overfitting. The blue curve shows the model's performance on the training data, and the orange curve shows its performance on the validation data—which is excluded during training to evaluate generalisation. A notable reduction in training and validation loss throughout the early epochs suggests that the model is learning efficiently. The validation loss, however, might plateau or even rise as the number of epochs increases, indicating that the model might be starting to overfit to the training set, even though the training loss is decreasing. Since the validation loss does not significantly rise compared to the training loss, the curve shapes show that the model has reached a suitable degree of training without experiencing severe overfitting. Based on these loss curves, the 1D-CNN model shows potential in predicting future SDG 1 scores. The comparatively constant validation loss shows that the model can

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successfully apply the knowledge it has gained from the training set to new data, demonstrating its capacity to generalise to new data. However, additional validation using a separate test dataset is required to fully evaluate the model's overall efficacy. Even though the loss curves indicate that the 1D-CNN model does a good job of predicting SDG 1 scores, more testing and improvement are necessary to guarantee its resilience and pinpoint areas needing development.

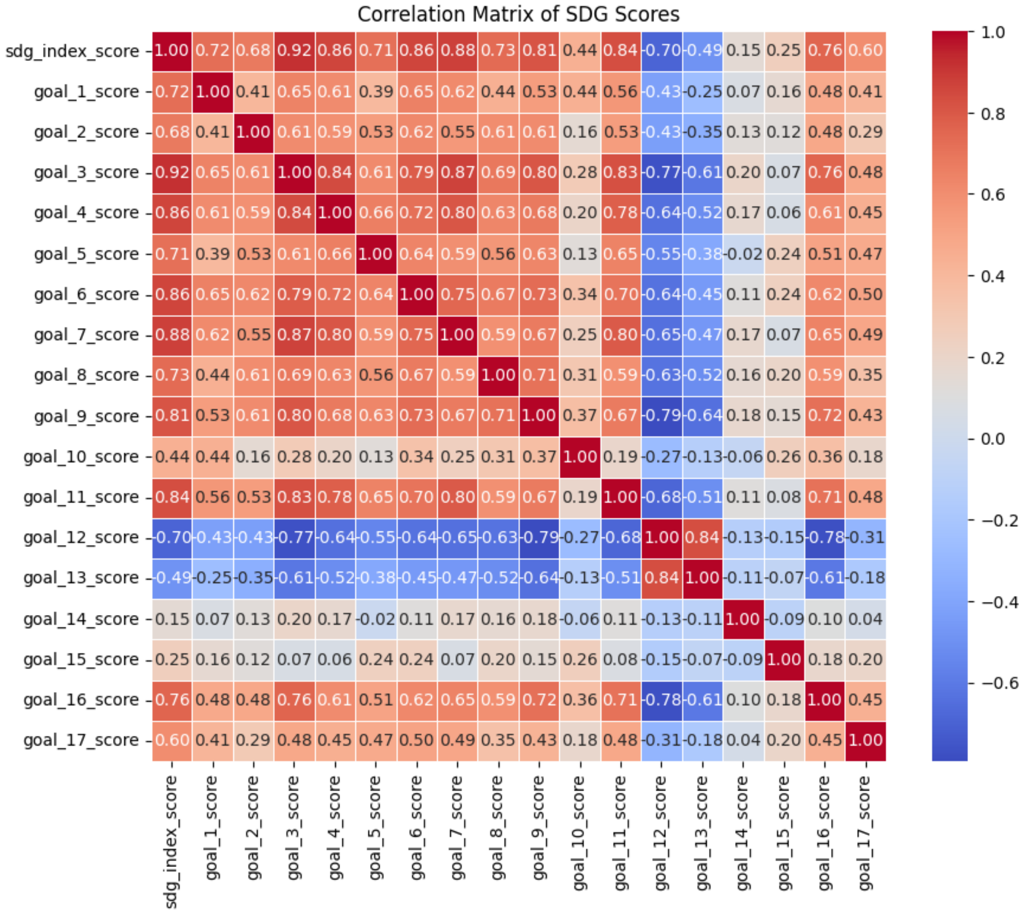

Figure 3. Correlation coefficients between the various SDG scores.

Forecasting Sustainable Development Goal 1 (SDG 1) scores are shown in Figure 5 to demonstrate the efficacy of the suggested methodology. The actual (historical) SDG 1 scores and the expected scores over different time steps are contrasted in each subplot. These time phases could include anticipating years in the future and training years in the past. The individual SDG 1 scores are displayed on the y-axis, most likely normalised within a predetermined range (e.g., 0 to 1). The red line shows the expected SDG 1 scores calculated by the 1D-CNN model.

Conversely, the blue line shows the actual SDG 1 scores, which either reflect historical data or act as a baseline for the forecasts. The close alignment of the red (predicted) and blue (actual) lines indicates that the model has a high capacity for prediction. The model's ability to accurately depict the underlying trends and patterns in the SDG 1 time series is demonstrated by its tight tracking. Some differences may occur, indicating that the model has trouble predicting specific values, even though most subplots show strong performance with little error between anticipated and actual scores. Because the model uses historical data as a time step to capture past associations and apply them to future forecasts effectively, the results highlight the significance of taking time-dependent patterns into account. Overall, the figure shows how well the model predicts SDG 1 scores, with most subplots showing high accuracy since the expected and actual values closely match. These findings can help stakeholders and policymakers make data-driven decisions and plan actions by giving them insights into expected future trends in poverty eradication, even though some variances may need more work.

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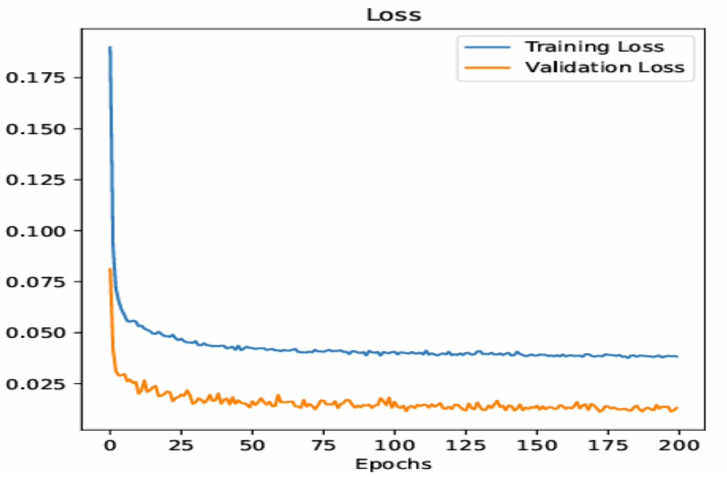

Figure 4. The training and validation loss curves for a 1D-CNN model.

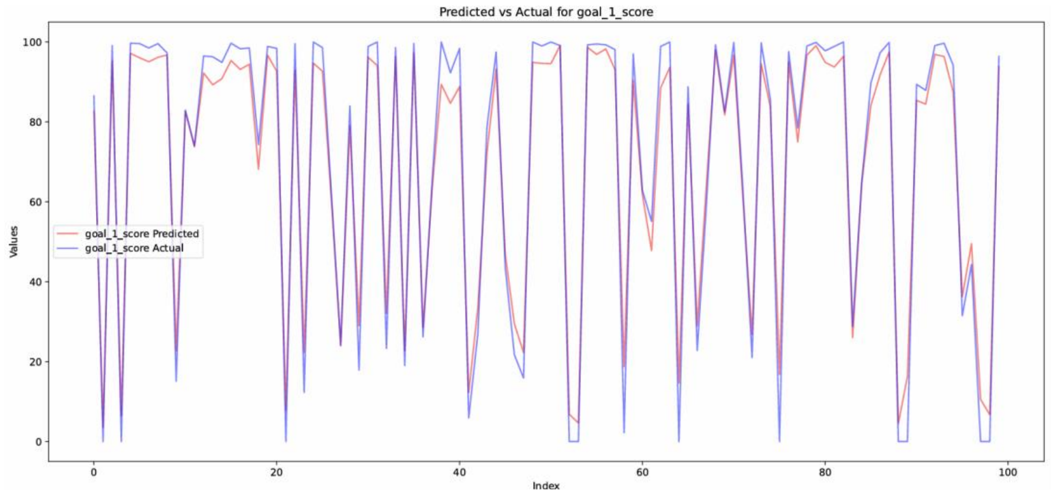

Figure 5. Comparison of actual and predicted SDG1

The Sustainable Development Goal (SDG) 1 scores for five significant nations—China, the US, Sweden, Saudi Arabia, and Egypt—for the years 2024–2030 are shown in this section. These countries were chosen because of their distinct methods for reducing poverty, varied socio-economic backgrounds, and different approaches to development. This analysis attempts to thoroughly grasp international efforts to end poverty by looking at nations from various geographical areas and with varying degrees of economic development. With a focus on social welfare and sustainable development, China, an economy expanding quickly, has made significant investments in efforts to reduce poverty. A distinct viewpoint is provided by the US, which strongly emphasises community-based initiatives and innovative social safety nets that try to lower poverty among underserved groups. Consistently praised for its extensive welfare system and high living conditions, Sweden exhibits successful policies that advance social justice and assistance for marginalised communities. Through its Vision 2030 plan, which includes measures to increase economic diversification and improve social services to lower poverty levels, Saudi Arabia is attempting to achieve SDG 1. Egypt, a rising country, is aggressively enacting reforms centred on access to essential services and economic inclusion to combat poverty.

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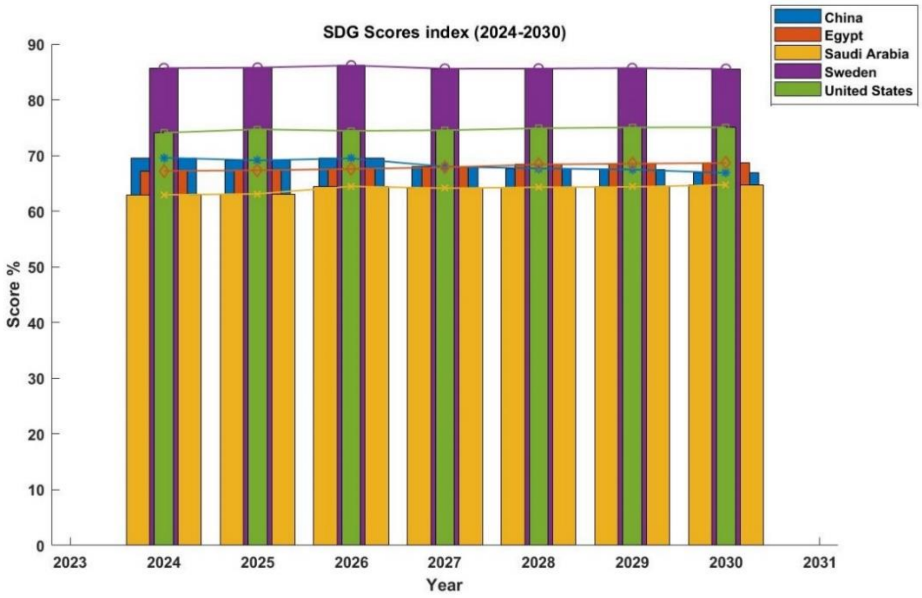

Figure 6. Predicted SDG Index Scores (2024-2030).

The Sustainable Development Goal (SDG) 1 Index Scores for China, Egypt, Saudi Arabia, Sweden, and the US are expected from 2024 to 2030 and are shown in Figure 6. With ratings above 80%, Sweden continuously performs best, demonstrating its advanced efforts in social welfare, poverty alleviation, and fair access to essential services. Although there are issues with addressing income inequality and access to social safety nets, the United States performs steadily, with scores ranging from 75% to 80%, showing consistent improvement in reducing poverty. Saudi Arabia, Egypt, and China all show comparable patterns, with scores between 65% and 75%. These rankings demonstrate the continuous efforts made in these nations to fight poverty using a range of measures, such as targeted poverty reduction programs, social service improvement, and economic diversification. These countries show steady progress, especially in raising living standards and expanding access to healthcare and education, even though their rankings are marginally lower than those of Sweden and the US. This graphic comparison highlights the differences in international efforts to accomplish SDG 1 and offers information on regional opportunities and difficulties that could affect the goal of ending poverty by 2030.

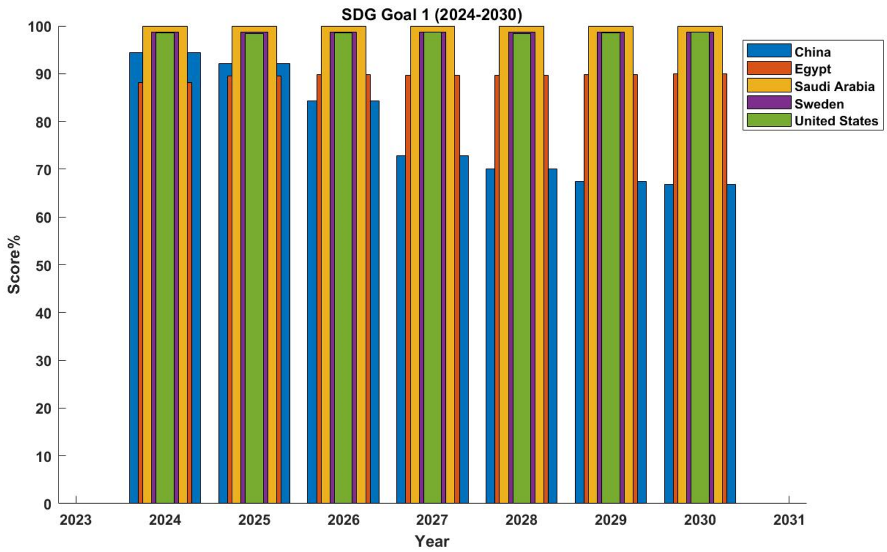

Figure 7. SDG Goal 1 (2024-2030).

The progress made by five nations—China, Egypt, Saudi Arabia, Sweden, and the United States—in achieving Sustainable Development Goal 1 (No Poverty) between 2024 and 2030 is graphically depicted in the bar chart shown in Figure 7. While the y-axis shows each country's percentage score for a given year, indicating its progress in reducing poverty, the x-axis depicts the historical timeframe, highlighting the years 2024–2030. The relative progress made in eradicating poverty can be assessed by comparing the heights of the bars for each country. The graph shows clear patterns in each nation's development, showing that whilst some have consistently made progress towards SDG 1, others have encountered major challenges. For example, Sweden's score has been steadily rising, which indicates the success of its robust economic policies, extensive social safety programs, and dedication to lowering inequality. The nation's strategy ensures that vulnerable populations receive sufficient help by integrating multiple areas, including social protection, healthcare, and education.

On the other hand, the pattern in the US is more erratic, with periods of advancement interspersed with periods of stagnation. The success of programs aimed at reducing poverty may be hampered by persistent issues like growing economic disparity and limited access to social safety nets, which this variability may indicate. The upward trend in China's bar chart highlights the country's significant efforts in social services, job creation, and rural development to rescue millions of people from poverty. The score shows there are still issues, especially when resolving the gaps between urban and rural communities. Saudi Arabia and Egypt show comparable trends, with scores rising moderately over time. Both nations have implemented specific measures to reduce poverty, like economic diversification plans and social safety nets. However, they still have issues with resource allocation and economic stability, which could hinder their capacity to make meaningful development by 2030. Overall, the graph highlights the various tactics and laws used to fight poverty and shows the five nations' differing levels of success. By analysing these variations, interested parties can learn essential lessons about what works and what needs to be improved, which will eventually direct future initiatives to end poverty worldwide.

Conclusion

The present research uses a robust time series forecasting model based on a one-dimensional Convolutional Neural Network (1D-CNN) to correctly project the Sustainable Development Goal 1 (No Poverty) scores for the years 2024 to 2030. The analysis's main subjects are the United States, Sweden, Saudi Arabia, Egypt, and China. Using deep learning techniques, the model leverages temporal connections in historical data from 2000 to 2022 to correctly estimate each country's progress towards eradicating poverty. The findings highlight the model's capacity to recognise and assess trends in poverty alleviation, allowing for accurate forecasts that correspond with expected worldwide trends in sustainable development. The methodology guarantees that the results are firmly rooted in the dynamics of historical performance connected to poverty reduction activities by limiting forecasts within a feasible range of 0 to 100. Apart from augmenting our comprehension of the diverse routes that culminate in eliminating poverty, this research offers significant perspectives for global organisations, interested parties, and governments committed to promoting programs to reduce poverty. The model is an essential tool for decision-makers, enabling nations to make well-informed decisions about the distribution of resources and calculated actions meant to accomplish SDG 1. To improve the precision and applicability of poverty estimates, future studies could expand on these findings by incorporating other socio-economic factors or investigating different modelling approaches. This could result in a more sophisticated comprehension of the potential and difficulties in ending poverty worldwide.

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