

Forecasting and Spatial Analysis of Sustainable Development Goals 1 and 4 Using TabNet

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ABSTRACT

This study applies the Tabular Neural Network (TabNet) to forecast and spatially analyze Sustainable Development Goals (SDGs) 1 and 4, providing evidence-based support for policymaking aligned with the United Nations 2030 Agenda. The dataset includes 3,841 observations from 167 countries, combining World Bank socio-economic indicators as predictors with SDG index scores as targets. A country-based split allocated 80% of countries for training and 20% for testing, ensuring cross-country generalization. Future projections for 2025–2030 use a persistence-based scenario in which socio-economic covariates remain at their most recent values, and lagged SDG scores are recursively updated, producing conditional simulations rather than purely autoregressive forecasts. The TabNet model demonstrates strong predictive performance: SDG 1 achieves RMSE of 4.22 (train) and 3.99 (test) with R^2 of 0.89 and 0.92, while SDG 4 achieves RMSE of 3.89 and 3.76 with R^2 of 0.95 and 0.93. Choropleth mapping highlights regional disparities, with higher predicted scores in Europe and North America compared to Sub-Saharan Africa. These results indicate that TabNet, combined with spatial visualization, provides an interpretable, robust, and policy-relevant framework for monitoring global SDG progress.

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1. INTRODUCTION

Tabular Neural Networks (TabNet) were introduced as a deep learning architecture specifically designed for tabular data [1], [2], [3]. This research is motivated by the need for an in-depth analysis of SDG performance levels and assessments of the Sustainable Development Goals (SDGs) [4], [5]. Monitoring SDG scores is essential for evaluating development progress and supporting global policy assessment by stakeholders, such as the United Nations, in measuring the success of countries in achieving established development indicators. This study focuses on SDG 1 and SDG 4 as key indicators representing poverty reduction and educational development. Previous studies indicate that understanding a country's SDG position supports evidence-based strategies to strengthen development pillars and identify gaps toward achieving the 2030 Agenda targets [6], [7].

Many previous studies have implemented machine learning and deep learning model architectures, in addition to Tabular Neural Networks, including [8], developed a forecasting model based on ARIMAX and Linear Regression to predict SDG scores until 2030. Its advantages are regional forecasting and the integration of smoothing techniques to improve prediction stability. However, the model used is still based on classical linear regression and time series, so it is less than optimal in capturing the complex nonlinear interactions between multidimensional and heterogeneous SDG indicators. Furthermore, research conducted by [9], through a systematic

literature review of 38 articles from 2019-2023 shows that the LSTM deep learning model is becoming the dominant approach in SDG forecasting due to its ability to capture temporal dependencies and improve prediction accuracy based on MAPE, RMSE, and R^2 metrics. However, LSTM is structurally designed for sequential data and is less specifically designed for tabular data with many features across social, economic, and environmental dimensions that do not always have strong temporal patterns.

Furthermore, research by [10], conducted the Sustainable Visions study, applying an unsupervised machine learning approach to analyze the interactions between SDGs in 107 countries over the period 2000-2022. This study shows strong positive and negative correlations between goals, as well as the influence of geographic and socio-economic factors on SDG achievement. The strength of this research is that it can reveal the systemic complexity of the SDGs globally. However, it is exploratory in nature and does not provide a future predictive model. Meanwhile, research [11], implemented a deep learning model based on LSTM [12], to predict energy demand within the framework of SDGs 7, 9, and 13, which confirmed that deep learning can improve prediction accuracy compared to traditional methods in the context of energy sustainability. Unfortunately, this research only focused on one sector and did not discuss the global integration of multi-indicator SDGs or cross-country spatial analysis.

Based on previous studies, a methodological gap remains in integrating tabular deep learning architectures for heterogeneous global panel data with spatially interpretable predictive analysis. Existing research typically focuses either on SDG correlation analysis or predictive modeling separately, and rarely combines tabular deep learning with spatial visualization for cross-country SDG forecasting, particularly for SDG 1 and SDG 4. Therefore, this study is important because it implements TabNet for forecasting and integrates spatial analysis in the prediction results. This approach captures nonlinear interactions between indicators and provides choropleth-based spatial visualization to identify global development inequality patterns [13], [14]. TabNet was used in this study because of its advantage in learning tabular data structures through a sequential attention mechanism capable of adaptively highlighting relevant features. This allows the integration to provide a strong methodological and practical contribution, more comprehensive than previous studies, in supporting data-driven policymaking towards achieving the 2030 SDGs agenda.

This study makes three main contributions; (1) constructing a global panel dataset integrating socio-economic indicators across countries and years; (2) developing a TabNet-based predictive framework for estimating SDG 1 and SDG 4 scores; and (3) integrating spatial visualization to support interpretable global SDG monitoring and policy-oriented analysis.

2. RESEARCH METHOD

This study adopts a quantitative experimental design combining predictive modeling and empirical evaluation using global SDG 1 and SDG 4 data from the World Bank. The research workflow consists of data collection, preprocessing (cleaning and normalization), dataset splitting into training and testing sets, model development, performance evaluation, and spatial analysis through choropleth visualization with Plotly Express, forming a continuous process as illustrated in Figure 1.

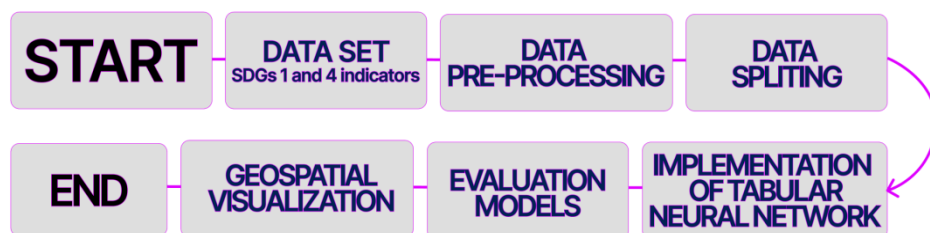


Figure 1. Research framework

This study combines two datasets from the World Bank. The first dataset, named “country summary.csv”, contains static country-level attributes and does not aggregate statistics

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across future years therefore, it does not introduce temporal information leakage. The second dataset named “country_data - Copy.csv”, includes detailed development data for many countries and their indicators. These two datasets were merged into a final integrated dataset used for modeling. The resulting dataset contains 3,841 observations spanning country and year dimensions, along with supporting indicators for SDG 1 and SDG 4. All country-level attributes were taken as static descriptors and were not computed using multi-year averages or future-period aggregation.

The dataset was then split using a country-splitting strategy that specifically allocated 134 countries as 80% for the training set, while the remaining 33 countries, or approximately 20%, were reserved exclusively for testing data. This strategy ensures that the model is evaluated on countries that have never been seen before, thus assessing cross-country structural generalization rather than temporal extrapolation. Although temporal dynamics differ across countries, the modeling framework assumes that structural relationships between socio-economic indicators and SDG performance follow common latent patterns learnable from the training countries. The TabNet model captures these shared nonlinear feature interactions while allowing for variation in magnitude and trajectory across national contexts. Therefore, its performance on previously unseen countries suggests that the model is learning generalized development patterns rather than memorizing country-specific trends.

The dataset is structured as panel data indexed by country and year (2000-2022). The variable country is encoded using ISO3 codes to ensure consistent identification, while year enables longitudinal tracking of development indicators. Predictor variables include life expectancy at birth, sex ratio, individuals using internet, school enrollment preprimary, school enrollment primary, school enrollment secondary, school enrollment tertiary, unemployment, gdp per capita growth, gdp growth, employment topopulation ratio, employment in industry, population, refugees unhr host country, mortality rate, and urban population growth. The target variables are goal 1 score (SDG 1 index) and goal 4 score (SDG 4 index). The integrated dataset was constructed by matching ISO3 country codes and yearly observations, resulting in a comprehensive panel dataset suitable for cross-country predictive modeling of SDG achievement. All predictor variables correspond strictly to the observation year of each record; no aggregated statistics computed using future-year information were included, ensuring that no temporal information leakage occurs during model training. This design ensures that future projections rely only on historically observed information, preventing leakage from unknown future covariates.

To support temporal continuity, the dataset includes lagged SDG variables representing the previous-year SDG scores. During forward projection, the initial lagged SDG values are taken from the latest observed year (2022). For subsequent projection years, lagged SDG inputs are updated recursively using the model’s predictions, while socio-economic covariates remain fixed under the persistence-based scenario. This design preserves temporal structure while ensuring that predictions remain primarily driven by structural covariate relationships rather than purely autoregressive dynamics. After data collection and integration, normalization was applied. This step ensures numerical stability and prevents scale dominance among heterogeneous indicators. Normalization also improves the convergence of deep learning models and ensures that the sequential attention mechanism in TabNet is not biased toward features with larger numerical ranges. Missing values were imputed using the median due to skewed distributions and the presence of outliers, as defined in Equations (1) and (2). All preprocessing operations (imputation, transformation, and scaling) were fitted using training data only and then applied to validation and test sets to prevent data leakage.

$$\text{Median} = x_{\left(\frac{n+1}{2}\right)} \quad (1)$$

$$\text{Median} = \frac{x_{\left(\frac{n}{2}\right)} + x_{\left(\frac{n}{2}+1\right)}}{2} \quad (2)$$

Outliers arise from countries with extreme conditions, such as countries experiencing conflict, countries with very high economic growth, or countries with unusual socioeconomic

characteristics. Outliers can disrupt the analysis and prediction process because they can lead the model to unrepresentative patterns. To detect outliers, is used equation (3) [15][16].

$$x' = \log(x + 1) \quad (3)$$

After the imputation and logarithmic transformation processes, feature normalization is performed using Min-Max Scaling to ensure that all attributes fall within the $[0, 1]$ range. This step ensures that each feature contributes equally to the model's learning process represented in equation (4). This step ensures that each variable contributes equally to the TabNet learning process[17][18].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (4)$$

After all data pre-processing was completed, the normalized distributions of SDG 1 and SDG 4 scores showed a strong right-skewed pattern, indicating that many countries achieved relatively high sustainability performance, while some remained lagging behind. For Goal 1, most observations were concentrated in the 0.85 – 1.00 range, with approximately 60–75% of data points exceeding 0.8, while a smaller proportion (approximately 10 – 20%) fell below 0.5, reflecting persistent global poverty disparities. Goal 4 showed a similar but more compact distribution, with approximately 70 – 85% of countries scoring above 0.8, indicating more homogenous global education development compared to poverty reduction. Furthermore, the narrower variance in Goal 4 compared to Goal 1 implies that education development is more equitable globally, while poverty reduction shows greater inequality across countries as illustrated in Figure 2.

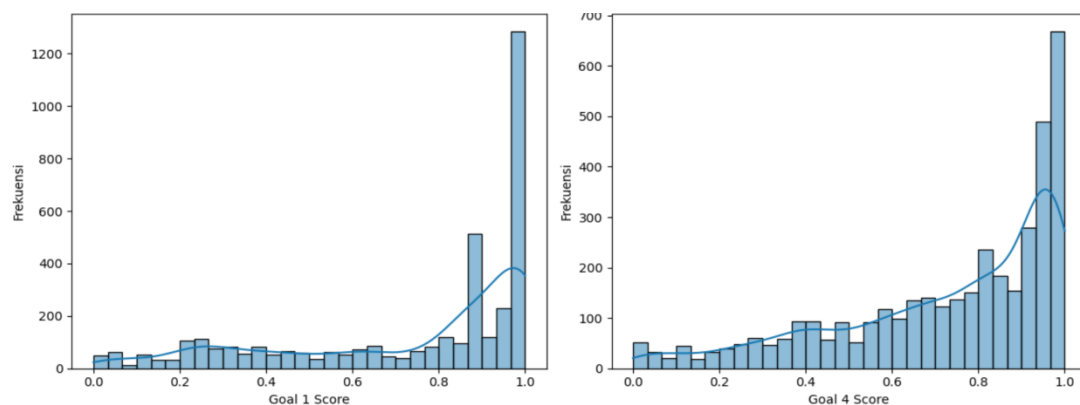


Figure 2. Distribution of Goal 1 Score and Goal 4 Score

Before implementing the TabNet model, a comparison was conducted with three baseline models: MLP Regressor, Gradient Boosting, and Support Vector Regressor, for predicting SDG 1 and SDG 4 (Tables 1 and 2). Note that the baseline models use original SDG scores (0–100), whereas TabNet uses normalized scores (0–1); therefore, MSE and RMSE values are not directly comparable in magnitude. On SDG 1, MLP Regressor showed the best performance with an MSE of 366.16, RMSE of 19.13, and R^2 of 0.72, indicating it explains 72% of the actual data variance. Gradient Boosting and Support Vector Regressor produced larger errors (MSE of 641.72 and 772.64, respectively) and lower R^2 values (0.52 and 0.42), making them less able to capture complex non-linear patterns in cross-country poverty indicators. A similar pattern is observed for SDG 4, where MLP achieved an MSE of 66.83, RMSE of 8.17, and R^2 of 0.90, outperforming Support Vector Regressor ($R^2 = 0.81$) and Gradient Boosting ($R^2 = 0.77$).

Table 1. SDG 1 with Comparative Modeling

Model	MSE	RMSE	R Square
MLP Regressor	366.16	19.13	0.72
Gradient Boosting	641.72	25.33	0.52
Support Vector Regressor	772.64	27.79	0.42

Table 2. SDG 4 with Comparative Modeling

Model	MSE	RMSE	R Square
MLP Regressor	66.83	8.17	0.90
Gradient Boosting	153.11	12.37	0.77
Support Vector Regressor	123.02	11.09	0.81

The results from Tables 1 and 2 show that the neural network approach is effective in representing nonlinear relationships between socio-economic indicators compared to boosting and kernel-based methods. However, although MLP[19] provides good performance, this model still utilizes all features at full density and lacks an adaptive feature selection mechanism, so its interpretability and efficiency on high-dimensional tabular panel data are still limited. Therefore, this study implements TabNet-Regressor through sequential attention and adaptive feature selection mechanisms. It starts with input features normalized using Batch Normalization (BN), then enters the main block that iterates. At each step, there are two core components: the Feature Transformer, which extracts nonlinear representations of features through several layers fully connected (FC), BN, and activation functions such as ReLU. The results are then split into two parts: one part is passed as the partial decision output, and the other part is used to construct a mask in the next step. The Attentive Transformer generates a feature mask that determines which features will be focused on at that step, so that only a subset of relevant features are processed further. This mask is multiplied with the previously aggregated features through the "Agg" block. This results in dynamic feature selection and controlled sparsity. The outputs from each decision step are summed to form the final representation, which is then passed to the FC layer to generate the final prediction. The TabNet mechanism is shown in Figure 3 [20], [21], [22].

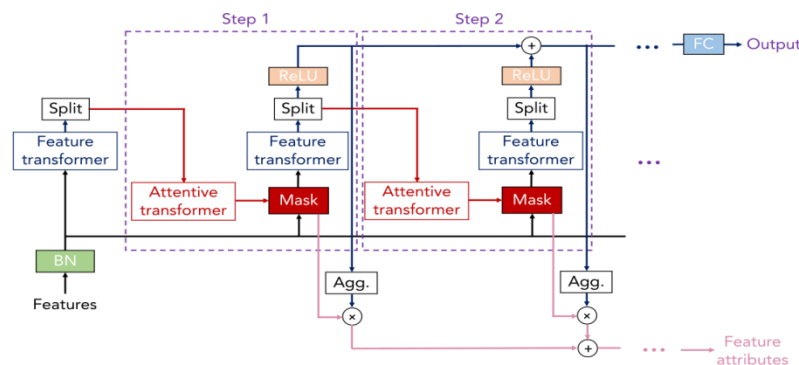


Figure 3. Architecture of the TabNet model

This capability makes TabNet more robust to the presence of missing values, unbalanced data distribution, and high inter-country variability in the SDGs dataset. Furthermore, this model is able to reduce the influence of outliers internally thanks to the normalization mechanism and selective attention masking of truly significant features. In terms of interpretability, TabNet also has advantages over conventional neural network models. In this study, predictive modeling for SDG 1 and SDG 4 was performed separately, where each SDG target was modeled using an independent single-output TabNetRegressor rather than a multi-task architecture. The model configuration uses representation and attention dimensions n_d of 16 and n_a of 16, which allows for efficient feature representation learning without excessively increasing model complexity. The decision-making process is carried out through 5 decision steps, where at each step the model selectively chooses the most relevant feature subset using a feature masking mechanism. A gamma parameter of 1.5 is used to control the degree of feature exploration between decision steps. The feature transformer structure consists of 2 shared layers and 2 independent layers to balance global and specific pattern learning at each step. Sparsity regularization is applied using λ_{sparse} of 1×10^{-4} to encourage interpretability by limiting the number of active features at each decision step. Optimization is performed using the Adam algorithm with an initial learning rate of 0.002, combined with the StepLR learning rate scheduler with a $step_size$ of 30, and a gamma of 0.9 to maintain convergence stability during the training process. The model was trained for a maximum of 300 epochs with an early stopping mechanism of 30 patience based on the Root Mean Squared

Error (RMSE) evaluation metric on the validation data. The training process used a `batch_size` of 512 and a `virtual_batch_size` of 128 to improve the stability of gradient estimation on large-scale datasets. After the training process, projections for 2025 – 2030 were generated using a covariate-driven scenario-based inference approach. The trained TabNet model predicts SDG scores as a function of socio-economic indicators and historical SDG values. For forward projection, the latest observed record (year 2022) is used as the baseline feature vector. Since future socio-economic covariates are not directly observed, this study adopts a persistence-based scenario in which covariate values are held constant at their latest available levels. Lagged SDG features are initialized using the most recent observed SDG values, and for subsequent projection years they are recursively updated using the model's previous predictions. Thus, each projection step combines fixed socio-economic covariates with dynamically updated lagged SDG indicators. Thus, for each projection year (2025 – 2030), the model input consists of fixed socio-economic covariates from 2022 and recursively updated lagged SDG scores from the previous prediction. Therefore, the resulting trajectories should be interpreted as conditional projections under stable socio-economic conditions rather than deterministic time-series forecasts. This design ensures that the model remains a tabular regression predictor driven primarily by structural covariate relationships rather than a purely autoregressive temporal model, as shown in Table 3 [23], [24].

Table 3. The code of Build and Training TabNet Model

Build Model	Training Model
<pre>regressor = TabNetRegressor(n_d=16, n_a=16, n_steps=5, gamma=1.5, n_independent=2, n_shared=2, momentum=0.3, lambda_sparse=1e-4, optimizer_fn=torch.optim.Adam, optimizer_params=dict(lr=2e-3), scheduler_params={"step_size": 30, "gamma": 0.9}, scheduler_fn=torch.optim.lr_scheduler.StepLR, seed=42, verbose=1)</pre>	<pre>regressor.fit(X_train, y_train, eval_set=[(X_test, y_test)], eval_name=["test"], eval_metric=["rmse"], max_epochs=300, patience=30, batch_size=512, virtual_batch_size=128, num_workers=0, drop_last=False)</pre>

Model performance evaluation is conducted by comparing the predicted results with the actual values of each target, using a series of quantitative metrics appropriate to the type of prediction task. The regression task aims to predict the numerical values of SDG 1 indicators (Goal 1 Score), and SDG 4 (Goal 4 Score). The evaluation is conducted using three main metrics, namely Mean Squared Error (MSE) which is used to measure the average squared difference between the actual value and the predicted value, thus providing a greater penalty for extreme errors due to the error squaring process represented in equation (6)[25].

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

Furthermore, the Root Mean Squared Error (RMSE) is the root of the MSE which returns the error units to the original scale of the data, so that it is easier to interpret as the magnitude of the prediction deviation from the actual value represented according to equation (7) [2].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

Lastly, there is the Coefficient of Determination (R^2) which is used to measure the proportion of data variation that can be explained by the model, with values close to 1 indicating very good predictive ability and high model fit to the actual data, represented in equation (8) [26], [27].

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (8)$$

To analyze the spatial distribution of predicted SDG indicators, a choropleth mapping approach was used. The predicted SDG scores generated by the TabNet model were geographically visualized using country-level ISO-3 codes. First, the prediction dataset was filtered to obtain predicted values for 2030. Country names were then converted to ISO-3 codes using the pycountry library to ensure compatibility with global geographic datasets. Countries without recognized ISO codes were excluded from the visualization process. A global choropleth map was then generated using Plotly Express to depict the spatial variation in predicted scores for SDG 1 and 4. The Viridis color scale was applied to represent the intensity of SDG performance, with darker colors indicating higher predicted SDG scores. This spatial visualization allows for comparative analysis of SDG progress across different regions and countries [28].

3. RESULTS AND DISCUSSION

The proposed TabNet model demonstrated strong predictive performance for SDG 1 and SDG 4. For SDG 1, the model achieved a Mean Squared Error (MSE) of 17.88 on the training set and 15.93 on the testing set. The corresponding Root Mean Squared Error (RMSE) values were 4.22 for the training set and 3.99 for the testing set. The coefficient of determination (R^2) reached 0.89 on the training set and slightly increased to 0.92 on the testing set, indicating strong explanatory power and stable generalization. For SDG 4, the MSE achieved 15.17 on the training set and 14.17 on the testing set. The RMSE values were 3.89 and 3.76 for the training and testing sets, respectively. The R^2 values reached 0.95 on the training set and 0.93 on the testing set, indicating that the model captures most of the variance in education-related development indicators. The close similarity between training and testing performance on both targets indicates that the model does not suffer from significant overfitting. Slightly higher test R^2 compared to training performance is attributed to variability in country distributions across folds rather than model overfitting. Instead, the model maintains stable predictive performance, as summarized in Table 4.

Table 4. The performance of TabNet SDG 1 and SDG 4

Type	MSE	RMSE	R Square
Train SDG 1	17.88	4.22	0.89
Test SDG 1	15.93	3.99	0.92
Train SDG 4	15.17	3.89	0.95
Test SDG 4	14.17	3.76	0.93

3.1. Predicted Trends of SDG 1 and SDG 4

Figure 4 presents exploratory visualization plots for several countries spanning 2024-2034 however, only projections for 2025-2030 are used for formal analytical interpretation. These plots are intended to enrich interpretation of possible long-term trajectory behavior, while the primary analytical focus of the study remains on the formal projection horizon of 2025-2030. Overall, the predicted trajectories can be grouped into three general patterns: stable-high performance countries, progressively improving countries, and medium-stagnant countries. SDG 1 predictions for several countries from the test set show heterogeneous temporal trajectories across countries with varying stability levels. Different dynamic patterns are seen but are consistent with the characteristics of each country's development level. Australia with code 9 shows high stability with predictions for Goal 1 remaining around 70 and Goal 4 in the 50s, reflecting relatively stable social conditions without significant fluctuations. The Bahamas with code 12 shows very high and stable performance, with Goal 1 approaching 100 and Goal 4 above 90, indicating very strong SDG achievement and a tendency to reach a plateau. Barbados with code 15 shows a progressive upward trend, especially for Goal 1, which spikes sharply around 2029-2030 before stabilizing above 90, while Goal 4 increases more gradually from the mid-70s to the late 80s, reflecting accelerated socio-economic development. Belarus, code 16, remains relatively stagnant at a medium level, with Goal 1 remaining around 40 and Goal 4 in the mid-40s, indicating slow and steady growth without

significant spikes. Belize, code 18, maintains a stable high performance, with Goal 1 in the early 90s and Goal 4 in the early to mid-80s, indicating consistent development gains. In contrast, Benin, code 19, shows a significant gap between the two goals, with Goal 1 remaining very high (near 100) and relatively flat, while Goal 4 remains around 70 with a slight gradual increase, indicating that while poverty indicators are under control, the education sector is still developing gradually. Overall, these patterns suggest that the model is capable of capturing heterogeneity across countries.

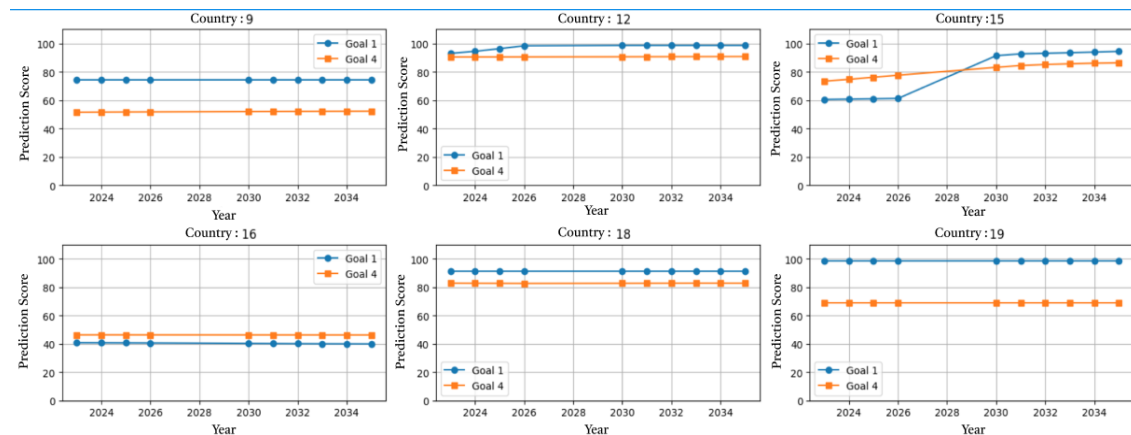


Figure 4. Predictions of SDGs 1 and 4 for 2024-2034 with TabNet

3.2. Spatial Analysis Mapping

Globally, higher predicted SDG scores are concentrated in Europe and North America, while lower scores remain visible in Sub-Saharan Africa and several developing regions. Specifically, the choropleth map shows that Indonesia's predicted SDG 1 index is 69.48, indicating moderate progress toward achieving the 2030 Sustainable Development Goals, as illustrated in Figure 5. As a developing country facing diverse socio-economic challenges, Indonesia requires responsive and sustainable policies to maintain and accelerate SDG progress. In this regard, [29] emphasizes that national commitment to SDG-related policies has strengthened under a more institutionalized regulatory framework through Presidential Regulations, although implementation challenges at the regional level remain significant.

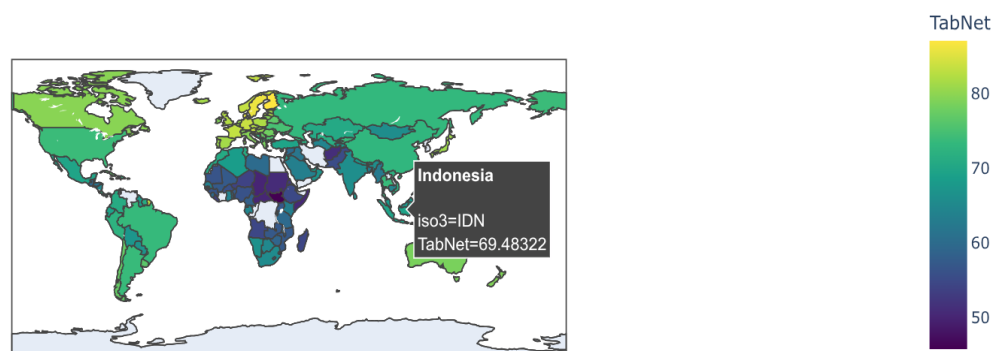


Figure 5. Predicted SDG 1 Index Score in 2030

Indonesia's predicted SDG 4 index is 69.12, indicating moderate progress toward achieving quality education targets. However, challenges in education quality persist, particularly in infrastructure, equitable access, and professional teacher capacity. This aligns with [30], who argues that SDG 4 not only provides a structured policy framework but also highlights the need for comprehensive efforts in policy implementation, funding allocation, and international cooperation to enhance the quality and equity of education, as shown in Figure 6.

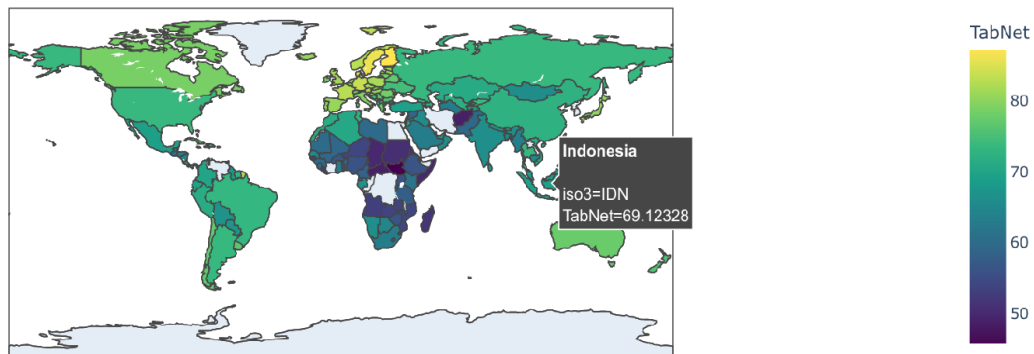


Figure 6. Predicted SDG 4 Index Score in 2030

4. CONCLUSION

This study demonstrates that the proposed TabNet model is capable of accurately predicting SDG 1 and SDG 4 indicators using complex, nonlinear global tabular data. The model achieves strong predictive performance, with MSE values of 17.88 and 15.93 for SDG 1 (training and testing), and 15.17 and 14.17 for SDG 4. The corresponding RMSE values remain below 4.3 across all settings, while R^2 values range between 0.89 and 0.95, indicating high explanatory power and stable generalization performance. Spatial visualization further highlights that countries in Europe and North America dominate with higher SDG scores, while Sub-Saharan African countries continue to lag behind. Overall, the integration of TabNet-based predictive modeling with spatial analysis provides a robust and policy-relevant analytical framework to support data-driven sustainable development planning. The projected SDG values for 2025–2030 represent model-based conditional simulations assuming stable socio-economic inputs and should not be interpreted as precise long-term forecasts or evidence of deterministic convergence patterns. The proposed framework emphasizes structural predictive relationships rather than strict time-series extrapolation. Future research could incorporate explainable artificial intelligence (XAI)[31] techniques to enhance interpretability and decision-support capabilities. These findings confirm the potential of TabNet as a scalable deep learning approach for global SDG monitoring using heterogeneous panel data.

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CONFLICT OF INTEREST

The authors declare that there are no known conflicts of interest regarding the publication of this paper. All author activities were conducted independently for academic and scientific purposes.

DATA AVAILABILITY

The data associated with this study are publicly available at <https://github.com/harfelyleipary/Data-Science-/tree/adfafe43fff065be1139e2ea2b1d1c044dfd153d/Kumpulan%20Dataset2>

AUTHOR CONTRIBUTIONS

First Author: Conceptualization; Data Curation; Data Labeling; Methodology; Investigation; Writing-Original Draft; Editing; Visualization; Project administration. **Second Author:** Conceptualization; Methodology; Investigation; Supervision; Validation; Writing-Review & Editing. **Third Author:** Conceptualization, Methodology; Investigation; Supervision; Validation; Writing-Review & Editing; Project administration.

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