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Neural Networks in Environmental Science: Forecasting CO_2 Emissions

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Abstract---The aim of the study is to analyze the performance of neural network models in predicting CO2 emissions across various regions, including major emitters such as China, the USA, the European Union, India, and Japan. Utilizing a dataset of carbon dioxide (CO2) emissions in the industrial sector from 2000 to 2022, the study employs three neural network models (LSTM); (RNN); (MLP); using Python for analysis. The results indicate that RNN consistently outperformed the other models, achieving the lowest mean square error (MSE) and root mean square error (RMSE). Country-specific analyses revealed significant challenges in India, where all models struggled, while RNN excelled in China and the United States. In contrast, Japan's LSTM model underperformed. Overall, CO2 emissions are projected to decline in India and China, driven by environmental policies and technological innovations, whereas emissions in the United States show only modest reductions. These findings highlight the importance of tailored forecasting approaches and effective environmental strategies for achieving sustainability.

Keywords---Prediction, CO2 emissions, Artificial intelligent, Neural network.

I- Introduction :

In recent years, various environmental issues have increasingly endangered human living conditions, including global warming, melting glaciers, rising sea levels, frequent extreme weather, Emissions of greenhouse gases, such as carbon dioxide (CO2) are the main cause of global warming. **(Jin, H. 2021).**
Global climate change is closely connected to the sustainable development of countries worldwide, which are actively seeking ways to mitigate further climate deterioration in the context of global

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warming. As concerns about climate change intensify, accurately forecasting carbon dioxide (CO2) emissions has become essential for policymaking and effective environmental management. The neural network, a computer technology developed in recent years, relies on its unique network structure characteristics and data processing methods to deliver fruitful results in various fields. Especially, using neural networks to build prediction models is a relatively common data processing method;

The current study aims to forecast the level of CO_2 emissions in the industrial sector for 2000 to 2022 at the following countries level: China(b), India(a), Japan(d), and the United States(c). CO2 emission is the key contributor to climate change and there is a global consensus that the mean global surface temperature must be contained at 1.5 degrees C above the pre-industrial level. Consequently, several countries have signed the Paris agreement to reduce emissions within their national boundaries. Against this backdrop, it is essential to forecast the CO2 emissions levels in the countries that emit a higher share. Such fore- casting will help the national governments to adjust their climate policies;
Traditional statistical methods, while useful, often fall short in capturing the complex, nonlinear interactions inherent in environmental systems. Recent advancements in artificial intelligence (AI) have opened new avenues for more precise and reliable forecasting techniques. We used three neural network models (LSTM); (RNN); (MLP); to predict future emissions several reasons

1- to select the best model for each country, which helped identify the most appropriate model for predicting future emissions based on the available data.
2- **Long Short-Term Memory (LSTM)** are particularly effective for time-series data because they can capture long-term dependencies. They are designed to remember information over extended periods, making them well-suited for predicting emissions that depend on historical trends.
3- **Recurrent Neural Network (RNN)**: are a powerful tool for analyzing and predicting sequential data, making them valuable in many domains, including climate modeling and emissions forecasting.
4- Multilayer Perceptron (MLP), is more efficient in capturing the nonlinearity present in the time series data and provides higher accuracy in forecasting the CO2 emissions based on the past values of the emissions; MLPs can be scaled by adding more layers and neurons, making them adaptable to different problem sizes and complexities;

The contributions of the paper are: 1- introduction and Literature review;
2- Materials and methods; 3- Analyzing performance of Neural network models for prediction of CO2 emissions; 4- training and testing of the model.
5 presents results and discussion. Finally; conclusion.
- This study is based on the applied and analytical approach.to address the following research questions:

How can neural network methodologies be leveraged to enhance the accuracy and effectiveness of CO2 emissions forecasting in environmental science, particularly in major global emitters such as China, the USA, India, and Japan?

II- Literature review:
Artificial intelligence (AI) has become an integral part of our daily lives, playing a crucial role in various fields, including environmental sustainability. AI has revolutionized the way we analyze vast amounts of environmental data, offering innovative solutions to the challenges posed by climate change and resource management. One prominent example is the use of AI models to forecast carbon dioxide emissions, which is essential for climate change mitigation and adaptation strategies **(Yangyang & Veerabhadran, 2017)**. AI-driven forecasts enable governments and industries to anticipate emission trends and implement timely interventions to meet global climate targets, such as those outlined in the Paris agreement **(V, M.L, D, & N, 2020)**.Traditional forecasting methods like statistical models have limitations in capturing the complexity of emission dynamics, **(Box G. E., Jenkins, Reinsel, &**

Ljung, 2015) which is where AI's predictive power excels. AI-based models, optimized through machine learning techniques like support vector machines, are highly effective in improving prediction accuracy **(Elif , 2014)**. These advanced models address the shortcomings of traditional methods, which often assume a linear relationship between variables and rely heavily on historical data. This linear approach fails to fully account for nonlinear factors like economic growth, technological advancements, or policy shifts, all of which play a crucial role in influencing CO2 emissions **(Kingsley , Jianguo , Rhoda , & Daniel , 2018)**. Furthermore, AI plays a significant role in predicting weather patterns and improving energy efficiency in smart cities. By analyzing data from sensors and environmental inputs, AI models improve the precision of weather forecasts, enhancing disaster preparedness and energy management **(Onyebuchi Nneamaka, et al., 2024) .** **(Ricardo, et al., 2020)** emphasize that AI-based energy optimization in urban environments reduces carbon footprints and improves resource utilization, contributing to smarter, more sustainable cities. Artificial Intelligence (AI) is revolutionizing environmental performance thanks to its ability to analyze huge amounts of complex environmental data in a short time and with high efficiency. In this context, AI is used to analyze multiple interactions between variables such as energy consumption, manufacturing, and transportation, contributing to a more accurate prediction of CO2 emissions. **(Marcelo & Kazuo , 2023)**.

Numerous neural network models have been utilized in order to accomplish this." such as CO2 flux modeling using crop types, soil temperature, soil moisture content, photosynthetically active radiation (PAR), and soil oxygen exchange using multiple linear regression (MLR) artificial neural networks and deep learning neural networks (DLNN). **(S. , 2021)** .Using the Artificial Neural Network (ANN) approach, which is a collective data processing method (GMDH), to determine carbon dioxide emissions, based on different energy sources used as primary energy supplies and GDP as an indicator of economic activity in Iran, Kuwait, Qatar, Saudi Arabia, United Arab Emirates, **(Mohammad Hossein, Hamidreza , Kwok-wing , Ravinder , & Marc A. , 2019)**.Two types of artificial neural networks (ANNs), Back Propagation Neural Network (BPNN) and Generalized Regression Neural Network (GRNN), were used to predict carbon dioxide (CO2) flux emissions from reservoirs **(Zhonghan , Xiaoqian , & Ping, 2018).** A nonlinear dynamic model embodied in the Multilayer Artificial Neural Network (MLANN) model was relied upon to obtain a prediction with a high level of accuracy. Using GDP, urban population ratio, and trade openness **(Pradyot Ranjan , Shunsuke , & Babita , 2021)**. Neural networks are a powerful and innovative tool in processing complex and non-linear environmental data, making them a promising option in improving the accuracy of CO2 emission predictions.

How can AI help to reduce C02 emissions?

Amid an accelerating global environmental crisis, carbon emissions from major countries are a major focus of the climate change debate. In 2023, global emissions are a mix of national pledges, industrial legacies, and emerging challenges. These emissions are not just numbers; they reflect the world's path to a low-carbon future. As advanced economies' GDP grew by 1.7%, emissions fell by 4.5%, an unprecedented decline outside of recessions. After a decline of 520 million metric tons, they returned to 1900 levels. As advanced economies' GDP grew by 1.7%, emissions fell by 4.5%, an unprecedented decline outside of recessions. After a decline of 520 million metric tons, they returned to 1900 levels. This decline in advanced economies' emissions is due to a combination of structural and cyclical factors, such as the massive expansion of renewable energy sources, the shift from coal to gas in the United States, weak industrial production in some countries, and mild weather conditions. Major countries such as China, the United States, India, and Japan play a crucial role in this context **(Figure 1)**. Carbon emissions in major countries are embodied in: **(Hannah , Pablo , & Max , 2024)** **(Laura , Annette , & CNN, 2024), (IEA, 2024).**

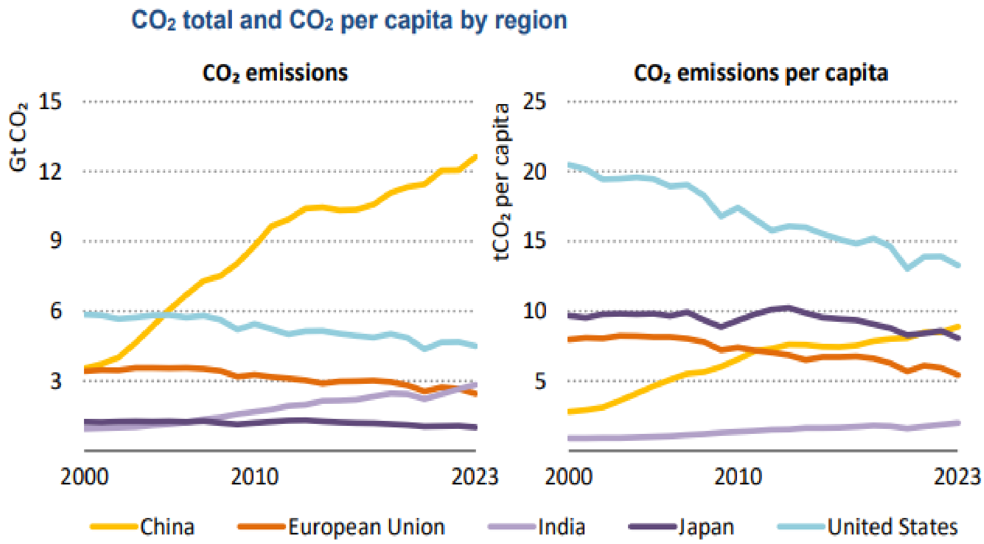


Figure 1: CO2 total and by region
Source: IEA, (2024), CO2 Emissions in 2023: Anew record high, but is there light at the end of the tunnel?
page 20, www.iea.org

✓ **China:** China is the world's largest CO2 emitter, contributing 32% of total emissions in 2023 at an estimated 565 million tons, the largest increase globally. These emissions are mainly attributable to the electricity and heat production, industry, and transportation sectors. Consumption-based emissions also show that China plays an important role in exporting products with a high carbon footprint that are consumed in other countries. China's per capita emissions are now 15 percent higher than advanced economies.

✓ **United States** Ranking second with 14% of total global emissions, its emissions come mainly from the electricity production, heating, transportation, and industrial sectors. If wind conditions were the same as in 2022, 16 million tons of CO2 could have been avoided in the U.S. in 2023. Despite the shortage of hydro and wind generation that affected the U.S., renewables in the electricity sector reduced
emissions by about 20 million metric tons. Had bad wind and hydro conditions not occurred, the deployment of renewables would have reduced emissions by about 40 million metric tons

✓ **India:** India ranks third with 9%, accounting for about 190 million tonnes of emissions, driven by strong GDP growth. A weak monsoon has increased electricity demand and reduced hydropower generation, contributing to about a quarter of the total emissions increase in 2023. However, India's per capita emissions remain well below the global average

✓ **Japan:** Japan contributes about 1.2 gigatonnes of CO2 emissions from sectors such as electricity and heat production, industry, and transportation. Consumption-related emissions reflect Japan's reliance on imported products with a high carbon footprint.

AI can play a crucial role in reducing CO2 emissions and improving the climate through several mechanisms, contributing to green development and reducing emissions as follows: **(Mingyue, Shuting , & Xiaowen, 2024) (Charlotte , 2021)**

- **Improving energy efficiency:** AI can help improve energy efficiency by analyzing big data, enabling better management of resources and reducing waste. For example, AI systems in industry are able to identify inefficient energy consumption patterns and suggest improvements to reduce consumption, leading to reduced carbon emissions.

- **Promote innovation in green technology:** By fostering technological innovation, AI encourages companies to develop environmentally friendly solutions such as the use of renewable energy technologies. AI also facilitates research and development in areas such as carbon capture and biodegradable materials, contributing to minimizing harmful environmental impacts.
- **Better infrastructure management:** Smart cities use AI to improve public transportation networks, traffic management, and energy savings in buildings, reducing the need for fossil fuels and lowering emissions.
- **Predicting climate risks:** Using machine learning techniques and analyzing climate data, AI can improve the accuracy of climate predictions. This enables governments and businesses to make proactive decisions to minimize environmental disasters and reduce emissions in the future.

III– Methods and Materials:

This article delves into the integration of neural network methodologies within the realm of environmental science, focusing specifically on the prediction of CO2 emissions in major emitters such as China, the USA, India, and Japan.
The dataset of carbon dioxide (CO2) emissions in the industrial sector from 2000 to 2022 was obtained from the International Energy Agency (IEA), and three neural network models were applied to predict future emissions:

1. Long Short-Term Memory (LSTM) network
2. Recurrent Neural Network (RNN)
3. Multilayer Perceptron (MLP), which are shown in the table below

The study sample included the following countries: China(b), India(a), Japan(d), and the United States(c). Predictive accuracy metrics were used to select the best model for each country, which helped identify the most appropriate model for predicting future emissions based on the available data."

Table 1: Architecture of the Applied Neural Network Models (MLP, RNN, and LSTM)

Model	Layers	Units per Layer	Activation Function	Regularization	Optimizer	Input Shape	Output Shape	Data Split (Train/Test)
MLP	Dense (64)	64	ReLU	Dropout (0.2)	Adam	12	1	70% / 30%
	Dense (32)	32	ReLU	-	Adam	12	1	
RNN	Dense (1)	1	-	-	Adam	12	1	
	SimpleRNN (50)	50	ReLU	Dropout (0.2)	Adam	(12, 1)	1	70% / 30%
	Dense (1)	1	-	-	Adam	(12, 1)	1	
LSTM	LSTM (50)	50	ReLU	Dropout (0.2)	Adam	(12, 1)	1	70% / 30%
	Dense (1)	1	-	-	Adam	(12, 1)	1	

Source: Prepared by researchers using the Python program

- ✓ Data Normalization: To increase model convergence during training, the MinMaxScaler was used to standardize the data within the range of 0 to 1.
- ✓ Data Splitting: Thirty percent of the data was utilized for testing and seventy percent of the data was used for training. This division guarantees a thorough assessment of the model's functionality.
- ✓ Time Window: Twelve months of data from the prior year served as the basis for each input sample for creating the input sequences.
- ✓ Data Reshaping: In order to account for temporal dependencies, the input data for the RNN and LSTM models had to be transformed into a 3D tensor, whereas the data for the MLP model was reshaped as a 2D matrix.

- ✓ Optimizer (Adam): Due to its effectiveness in managing sparse gradients and little need for hyperparameter adjustment, the Adam optimizer was applied to all models. Adam integrates the benefits of RMSProp and the Adaptive Gradient Algorithm (AdaGrad).
- ✓ Performance Metrics: To assess the models' training and testing accuracy, RMSE, MAE, and R2 values were used.
- ✓ Future Prediction: Using the final time window from the training data, each model was used to project the upcoming 36 months.
- ✓

IV- Results and Discussion

IV.1. Results:

❖ **Analyzing performance in India:**

Neural network models in India showed mixed performance, with results indicating moderate accuracy in predicting CO2 emissions:

1. **MLP**: The performance of the MLP neural network model was lower than expected, indicating that it may not be best suited to handle the temporal patterns in the Indian CO2 emissions data.
2. **RNN**: Provided better results, with a greater ability to learn from previous information. This performance can be attributed to the properties of RNN that allow it to adapt to temporal sequences.
3. **LSTM**: LSTM scored poorly, which may indicate that the model was unable to handle the complex data in the context of Indian emissions.

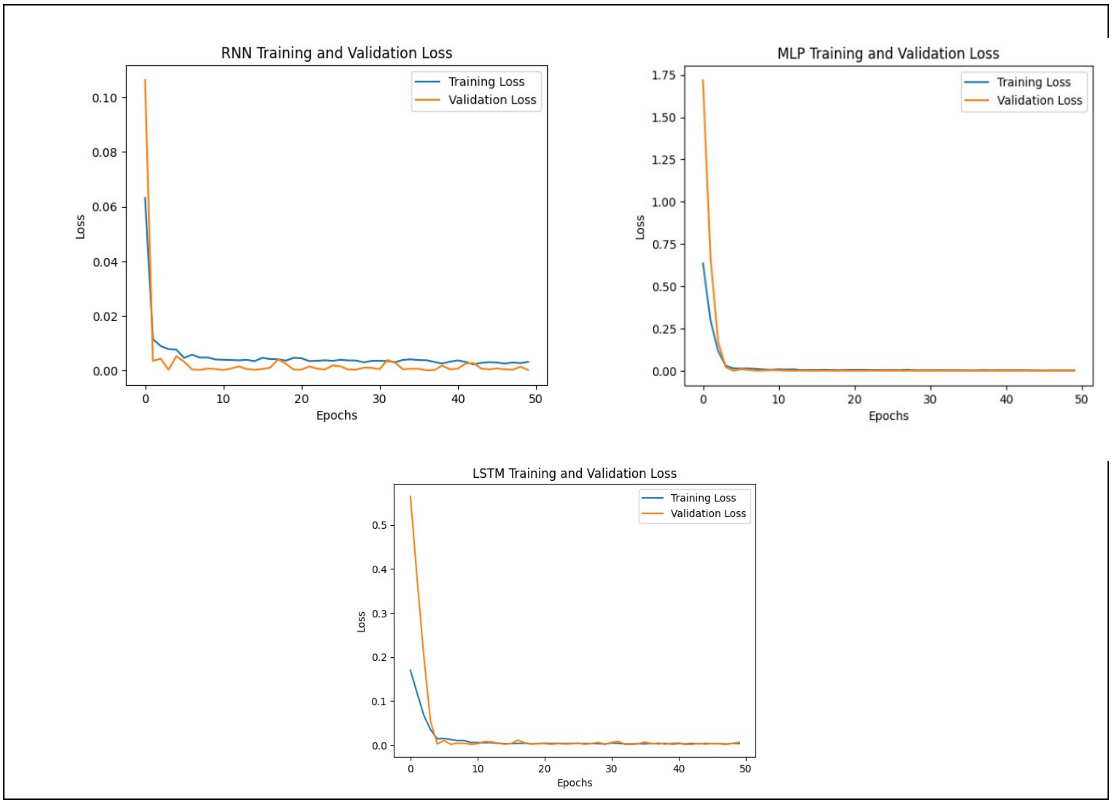


Figure 2: The training and testing outputs of the applied neural network models in India
Source: Prepared by researchers using the Python program

❖ **Analyzing performance in China:**

In China, the results point to similar challenges to those faced by India. China is one of the largest industrializing countries, leading to high and complex emissions.

1. **MLP**: This model showed average performance, suggesting that it may need improvements or modifications to better fit the nature of the data.
2. **RNN**: The model showed better performance than MLP, reflecting the usefulness of using recurrent networks to capture temporal patterns in industrial data.
3. **LSTM**: This model did not achieve the expected success, indicating that the factors influencing emissions in China may be more complex.

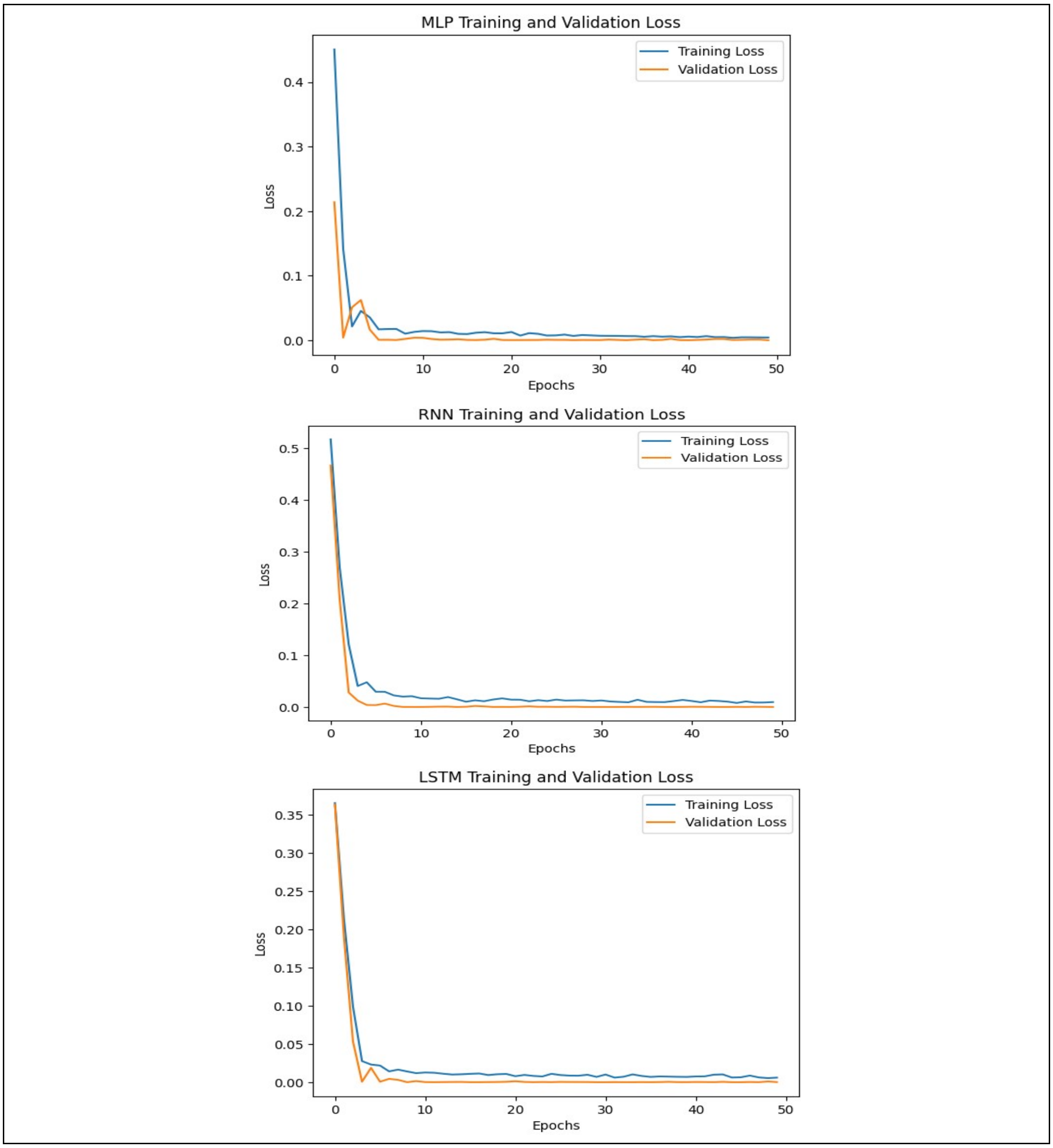


Figure 3: The training and testing outputs of the applied neural network models in China
Source: Prepared by researchers using the Python program

❖ **Analyzing performance in the United States:**

The U.S. showed good results overall, reflecting the strength of neural network models in handling emissions data in a more stable environment.

1. **MLP**: Showed reasonable accuracy, but was not the best.
2. **RNN**: Was the most successful model, indicating that the US emissions data has a temporal pattern that can be well exploited by these models.
3. **LSTM**: Although the performance was not as expected, the results were better compared to some other countries. This good performance can be attributed to the availability of comprehensive and accurate data.

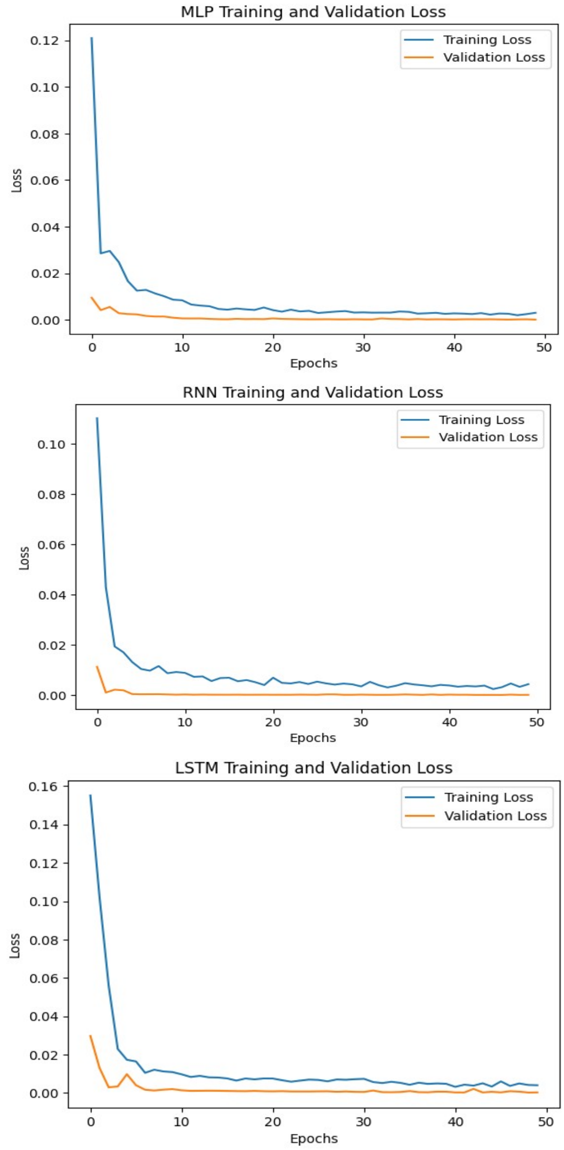


Figure 4: The training and testing outputs of the applied neural network models in Usa
Source: Prepared by researchers using the Python program

❖ **Analyzing performance in Japan:**

Japan, being a developed country, has well-developed environmental and industrial systems, which is reflected in its data.

1. **MLP**: Performance was acceptable, indicating that the model needs improvement.
2. **RNN**: Achieved good results, which can be attributed to its ability to learn from temporal patterns and changes in the data.
3. **LSTM**: The model achieved less accuracy in training and testing, and showed its inability to learn from complex data. This can be attributed to efforts in developing environmental strategies in Japan

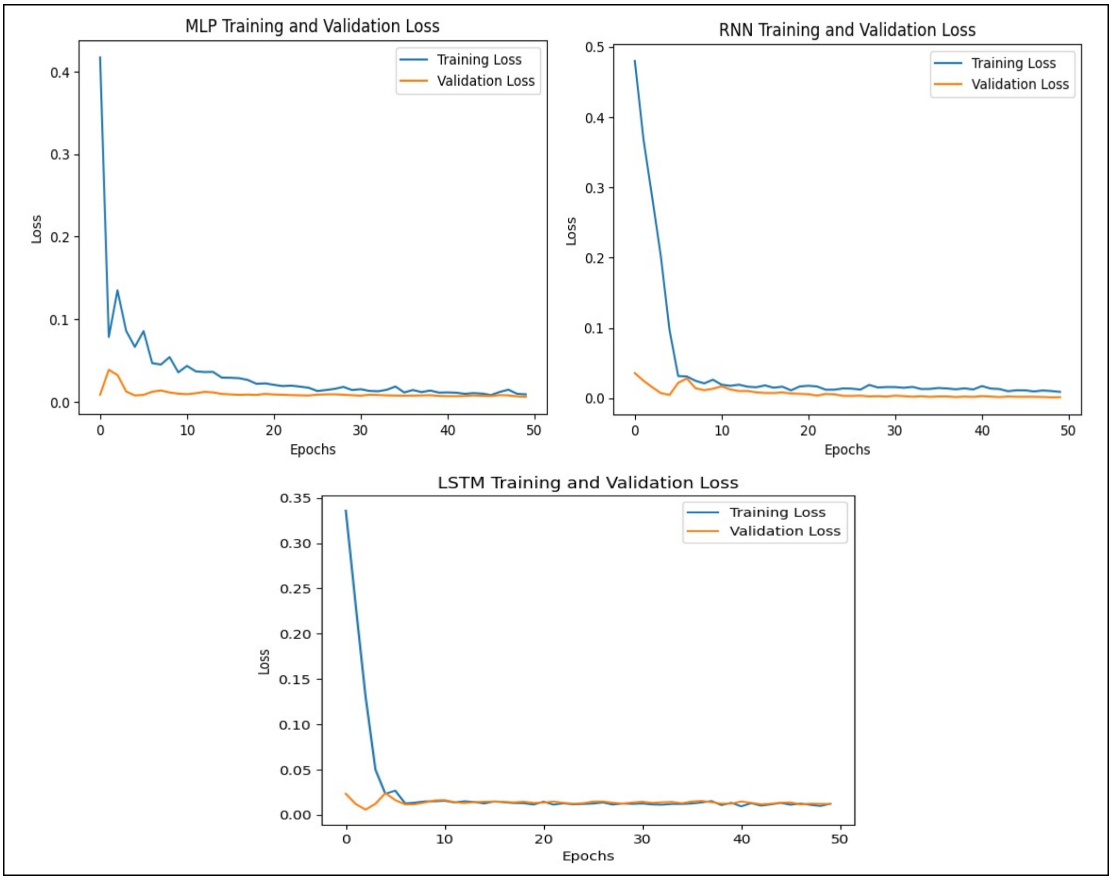


Figure 5: The training and testing outputs of the applied neural network models in Japan
Source: Prepared by researchers using the Python program

IV.2. Compare the models applied in the study:

Overall performance of the models

The results showed significant variation in the performance of the models by country. The recurrent neural network (RNN) showed superior performance in most cases, while achieving low values for performance indicators such as mean square error (MSE) and root mean square error (RMSE). In contrast, MLP was less efficient, especially in India and China, where negative values of the coefficient of determination (R^2 Score) indicate the model's inability to properly explain the variability in the data.

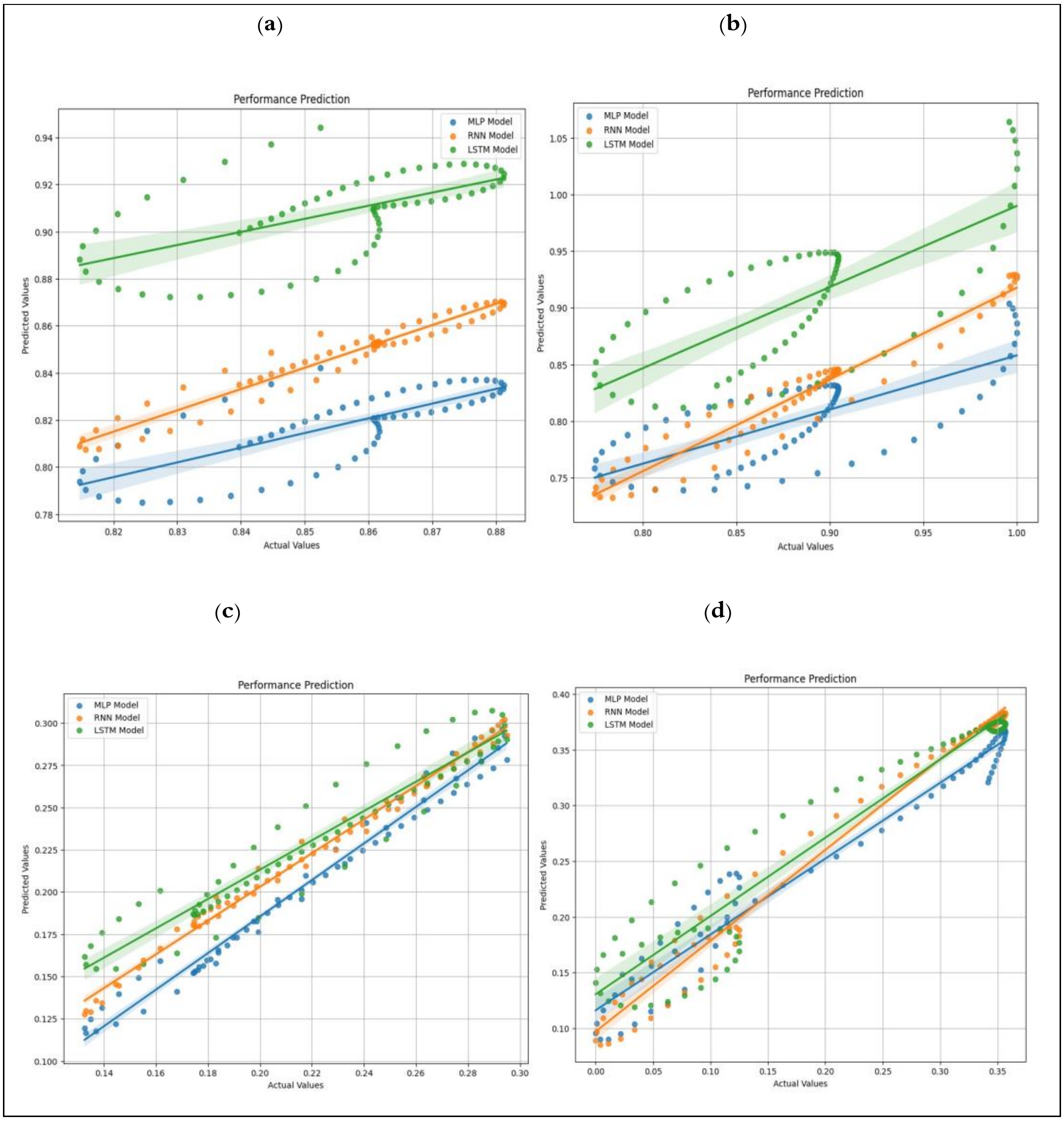


Figure 6: Predictions vs. actual values for different models (India; China; Usa; Japan)
Source: Prepared by researchers using the Python program

- **Analyzing performance by country**
  - **India**: All models showed relatively poor performance, with MLP and LSTM achieving high MSE and RMSE values. These results reflect the economic and environmental challenges facing India, such as rapid population growth and industrial changes. RNN was the most effective, but it was not enough to overcome the complexities of the data.
  - **China**: RNN achieved outstanding performance with the lowest values of error indices. However, LSTM showed a negative value in the coefficient of determination, indicating its unsuitability for Chinese data. These results suggest that neural network models may need to be customized to suit local idiosyncrasies.
  - **United States of America**: RNN was the most successful model, achieving the highest coefficient of determination value (R^2 Score) indicating that the model was able to explain 94%

of the variance in the data. While MLP and LSTM showed reasonable performance, RNN was the most accurate.

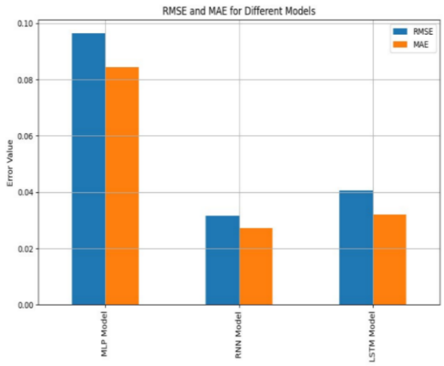
o **Japan**: Despite being a developed country, LSTM did not perform well, showing that there are factors affecting the performance of the model. RNN and MLP were the most effective.

Table 02: Comparison of different applied neural network models

Model Performance		**Contry**			
		India	China	Usa	Japan
MLP	MSE	0.0093	0.0066	0.0004	**0.0067**
	RMSE	0.0964	0.0815	0.0192	0.0821
	MAE	0.0843	0.0798	0.0171	**0.0624**
	R^2 Score	-1.3034	-17.4148	0.8427	0.6249
RNN	MSE	**0.0010**	**0.0000**	**0.0001**	**0.0052**
	RMSE	**0.0317**	**0.0069**	**0.0100**	0.0722
	MAE	**0.0273**	**0.0053**	**0.0087**	0.0632
	R^2 Score	**0.7513**	**0.8669**	**0.9576**	**0.7101**
LSTM	MSE	0.0016	0.0006	**0.0002**	0.0093
	RMSE	0.0405	0.0247	**0.0138**	0.0966
	MAE	0.0321	0.0220	0.0125	0.0764
	R^2 Score	0.5937	-0.6926	0.9184	0.4802

Source: Prepared by researchers using the Python program

(**a**)



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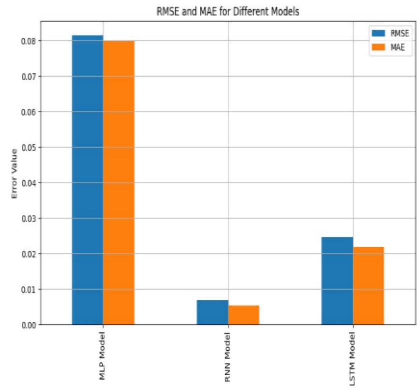
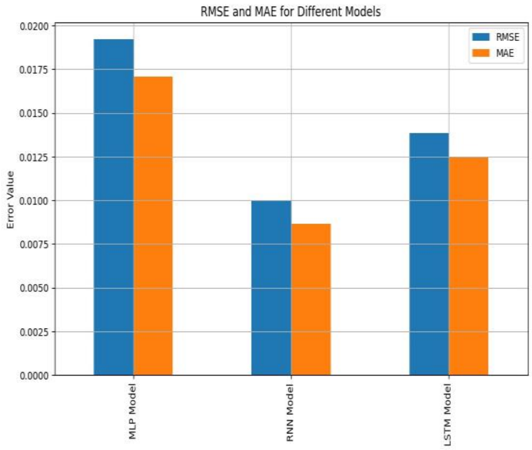


(**c**)



(**d**)

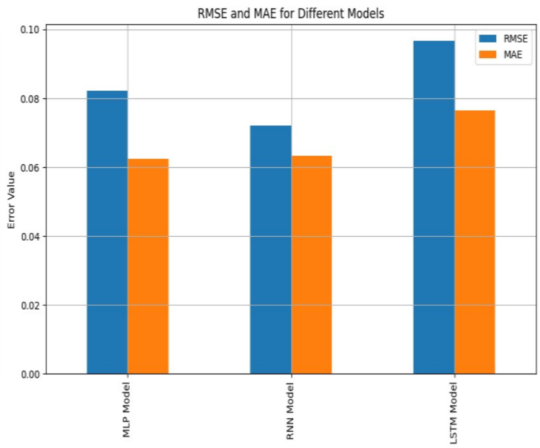


Figure 7: compares the neural network models employed in India, China, Usa and Japan based on the prediction study's indicators."
Source: Prepared by researchers using the Python program

IV.3. Forecasting carbon dioxide emissions in the industrial sector based on the optimal model for each country:

The table represents the projected values of carbon dioxide (CO2) emissions in the industrial sector from January 2023 to December 2025 in four major countries: India, China, the United States, and Japan.

- **Comprehensive statistical analysis**

A. General trends

Declining CO_2 emissions: The table indicates a general downward trend in CO_2 emissions in all countries except Japan, which shows relative stability.
India and China: Both countries show a notable decrease in CO_2 emissions, reflecting the impact of efforts towards improving energy efficiency and shifting to renewable energy sources.

b. Variation in performance between countries

- ✓ **India**: Its emissions are expected to decrease from around 599,960 in January 2023 to 489,159 by December 2025. This decrease is attributed to shifts in industrial policies towards clean energy sources.
- ✓ **China**: The forecast shows a decrease from 2696.896 to 2466.460, reflecting the government's strong actions to reduce industrial emissions, such as promoting the use of renewable energy and reducing pollution.
- ✓ **United States of America**: The pattern of emissions shows a slight decrease from 451.435 to 441.573. Despite this decrease, the pace of decline is slower compared to other countries, indicating challenges in meeting emission reduction targets.
- ✓ **Japan**: CO_2 emissions are stabilizing in a narrow range, with a forecast of 186,039 at the end of the period. This stabilization may reflect a trend toward sustainability and innovation in technology, but it may also indicate a lack of major changes in industrial infrastructure.

- **Economic explanation**

A. Trends in CO_2 emissions

India and China, two of the largest CO_2 emitters, are projected to make progress in reducing emissions. This can be attributed to:

- ✓ Environmental legislation: Such as policies that encourage the use of renewable energy.
- ✓ Technological innovations: Such as improved production efficiency and emission control technologies.
- ✓ Economic transformations: Such as shifting from heavy industries to lower-emission services or technologies.

B. Country responses to environmental pressures

- ✓ China: As the largest exporter, its figures may reflect government efforts to reduce emissions to meet the goals of the Paris Agreement.
- ✓ India: India is also taking steps toward reducing its emissions by investing in solar and wind energy, promoting sustainable development.

C. Economic influencing factors

- ✓ Economic growth: Low CO_2 emissions in India and China indicate sustainable economic growth, as these countries seek to balance industrial growth with environmental protection.
- ✓ Orientation towards sustainability: In the context of climate change, these data are positive indicators of countries' willingness to rely on clean energy, reflecting a shift in industrial policies.

Table 03: Forecasting CO_2 emissions in industry based on the optimized model for each country:

Month	RNN Predictions India	RNN Predictions China	LSTM Predictions Usa	MLP Predictions Japan
31/01/2023	599.960	2696.896	451.435	178.799
28/02/2023	595.770	2690.022	451.165	178.351
31/03/2023	591.203	2681.646	450.594	179.046
30/04/2023	585.927	2673.646	449.733	178.910
31/05/2023	580.487	2664.656	448.594	179.384

30/06/2023	575.214	2655.915	447.187	179.812
31/07/2023	569.899	2647.276	445.549	179.985
31/08/2023	564.590	2638.797	444.025	179.384
30/09/2023	559.507	2630.430	442.409	180.261
31/10/2023	554.615	2622.294	440.709	181.351
30/11/2023	549.901	2614.262	439.032	181.310
31/12/2023	545.382	2606.398	437.465	181.635
31/01/2024	541.066	2598.723	435.994	181.924
28/02/2024	536.979	2591.256	434.440	182.506
31/03/2024	533.103	2583.959	433.038	182.729
30/04/2024	529.436	2576.837	431.901	182.900
31/05/2024	525.978	2569.886	431.083	182.950
30/06/2024	522.720	2563.111	430.815	183.420
31/07/2024	519.654	2556.503	430.978	183.572
31/08/2024	516.773	2550.060	431.424	183.683
30/09/2024	514.069	2543.775	432.154	183.957
31/10/2024	511.533	2537.646	441.107	184.1441
30/11/2024	509.154	2531.668	434.347	184.390
31/12/2024	506.926	2525.836	435.678	184.501
31/01/2025	504.840	2520.155	437.089	184.691
28/02/2025	502.887	2514.618	438.529	184.832
31/03/2025	501.060	2509.222	439.903	185.043
30/04/2025	499.351	2503.963	441.107	185.107
31/05/2025	497.754	2498.838	442.068	185.265
30/06/2025	496.261	2493.845	442.736	185.398
31/07/2025	494.866	2488.979	443.087	185.514
31/08/2025	493.564	2484.239	443.110	185.635
30/09/2025	492.347	2479.619	442.883	185.725
31/10/2025	491.210	2475.118	442.611	185.847
30/11/2025	490.149	2470.733	442.148	185.933
31/12/2025	489.159	2466.460	441.573	186.039

Source: Prepared by researchers using the Python program

The projections indicate that all four countries are on track to meet CO2 emission reduction targets, with significant variation in the rates of reduction. The results highlight the importance of innovation and commitment to environmental policies, reflecting the shifts needed to achieve sustainable development in the context of a changing global economy, as illustrated in the figure below:

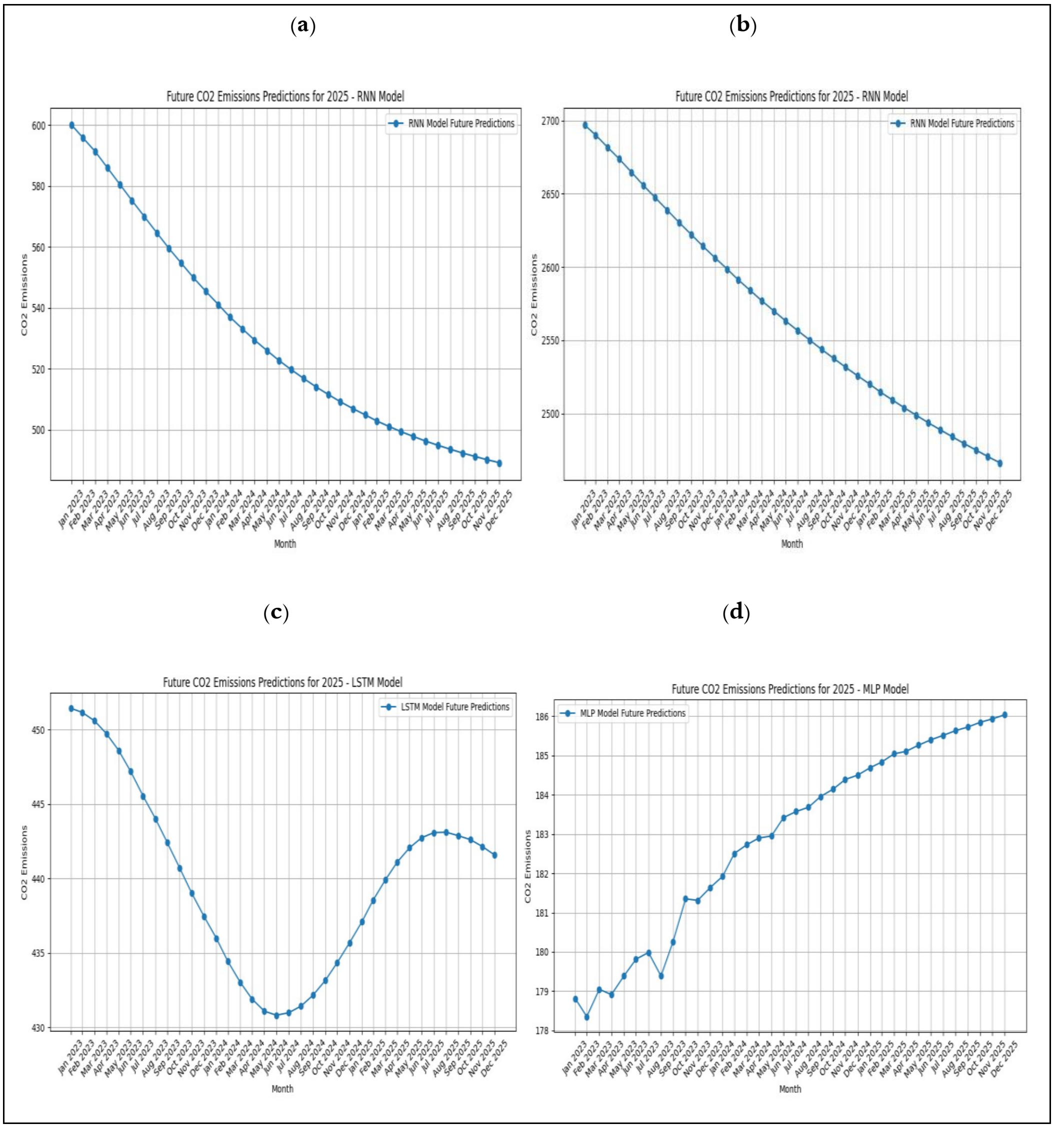


Figure 8: Forecasting CO2 emissions in industry based on the optimized model for each country
Source: Prepared by researchers using the Python program

V- Conclusion:

This study demonstrates that advanced neural network models, particularly RNN, LSTM, and MLP, significantly improve the accuracy of carbon emissions forecasting. The RNN model showed the best performance across various countries, while the other models faced challenges, particularly in India and Japan.

The projections suggest a general decline in CO2 emissions, driven by effective policies and clean energy initiatives, particularly in India and China. However, unique regional factors must be considered to enhance model effectiveness. Overall, these findings underscore the critical role of innovative forecasting techniques in supporting informed policy decisions and promoting sustainable practices to address climate change.

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