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FORECASTING CARBON DIOXIDE EMISSIONS: A DATA SCIENCE APPROACH TO AWARENESS AND MITIGATION

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ABSTRACT

A current major environmental issue of today's world is climate change and global warming, which are mainly driven by the increase in carbon dioxide (CO_2) concentration in the atmosphere, which is also the top contributor of greenhouse gases. According to the Paris climate conference agreement in 2015, the global temperature rise must be limited to 2 degrees Celsius while making the best effort to keep it at 1.5 degrees Celsius by the end of this century. So, reliable forecasting of CO_2 gas concentration in the atmosphere is necessary for planning and adapting mitigation strategies. While most of the studies only focus on forecasting, our research extends beyond forecasting to include impact assessment and recommendations for awareness and mitigation plans. In this study, we compare the performance of the deep learning models (LSTM, A-LSTM) with the statistical seasonal autoregressive model for time series forecasting of global CO_2. Our research demonstrates that the SARIMA outperformed both the LSTM and A-LSTM models, achieving an MAPE of 0.06% and RMSE of 0.33 compared to A-LSTM's 2.43% MAPE and LSTM's 2.74% MAPE. By providing reliable forecasting of CO_2 concentration, our research contributes to the Sustainable Development Goal (SDG) 13, which is Climate Action, enabling policymakers to make timely mitigation strategies.

Keywords: *Carbon dioxide, climate action, SD goal, deep learning, awareness creation*

1. INTRODUCTION

Forecasting carbon dioxide (CO_2) emissions is crucial for understanding future climate change and developing effective mitigation policies (Alsharkawi et al., 2025). Accurate prediction models enable policymakers to anticipate emission trends and take practical actions. Recently, machine learning techniques, particularly Long Short-Term Memory (LSTM) networks (Rafi et al., 2024), have been widely employed for CO_2 forecasting due to their ability to capture complex, nonlinear relationships (Wen et al., 2023). However, traditional statistical models, such as the Seasonal Autoregressive Integrated Moving Average (SARIMA), still demonstrate strong forecasting ability, especially in datasets that contain seasonal patterns (Park & Yang, 2024). Research shows that SARIMA models can effectively predict atmospheric CO_2 concentrations by capturing both long-term trends and seasonal changes (Gogeri et al., 2024). This suggests that SARIMA's ability to account for seasonality makes it a robust method in specific real-world applications.

Along with forecasting efforts, mitigation strategies are essential for tackling CO_2 emissions. These strategies include improving energy efficiency, expanding renewable energy sources, implementing carbon capture and storage technologies, and adopting policies such as carbon taxes and emission trading systems. Energy efficiency measures have significant potential, but renewable energy is still underutilised in many areas (Aguir Bargaoui, 2019). It is also recommended to have coordinated international efforts and joint projects to reduce emission costs, particularly in industrial and developing countries (Martin, 2000).

Unlike emission inventories that track economic activity and sector outputs, the concentration of CO_2 in the atmosphere has a direct impact on climate forcing and how global temperatures respond (IPCC,2021). The international climate goals outlined in the Paris Agreement are centered around temperature limits. These limits are more closely tied to the overall levels of atmospheric CO_2 concentration rather than just the annual emission rates (Nunes, 2023; Gogeri et al., 2024). This means that forecasting global CO_2 concentrations provides policymakers with a clearer and more pressing indication of climate risks, the shrinking carbon budget and the urgent need for mitigation efforts.

Time-series forecasting of CO_2 emissions has been studied using various statistical and machine learning models. For example, Kumari and Singh (2023) employed six models, including ARIMA, SARIMAX, Holt-Winters, linear regression, random forest, and LSTM, to analyse India's CO_2 emission data from 1980 to 2019. Their research showed that LSTM achieved the lowest mean absolute percentage error (MAPE) of 3.101%. Similarly, Luo (2023) compared the Prophet, ARIMA, and LSTM models using historical CO_2 data from 1750 to 2017 across various countries. They predicted that emissions would continue to rise. Their result also indicated that LSTM performed best among the other models (Rafi et al., 2024). Both studies showed the potential of deep learning models in time series forecasting (Rafi & Sohan, 2024).

Other studies have examined various variations of LSTM and hybrid models in multiple settings. Mountzouris et al. (2025) focused on indoor air quality. They used an attention-based LSTM to predict CO_2 concentrations in a Greek hospital. Their research showed that the attention-LSTM performed more efficiently than the standard LSTM model, obtaining a mean absolute error of about 8.9 ppm for 15-minute predictions. In a regional application, Wen et al. (2023) proposed a hybrid model for forecasting China's CO_2 emissions, which consists of ARIMA and LSTM. Their results indicated that the hybrid model outperformed both single models. Similarly, Zhang (2023) applied both ARIMA and LSTM separately on greenhouse gas emission data from 1990 to 2018. The study found that ARIMA captured the trend and seasonal patterns more effectively.

While previous studies on CO_2 forecasting have primarily focused on national or regional emission trends, employing statistical models such as ARIMA and Prophet or hybrid deep learning approaches (Luo, 2023; Wen et al., 2023; Alsharkawi et al., 2025), there is no justification on whether those models are able to directly capture the evolution of the global CO_2 concentration. So, despite the recent success in CO_2 forecasting, none of the cited works focused on predicting the world's atmospheric CO_2 concentration and suggesting mitigation plans accordingly. Our research fills this gap by creating effective models for forecasting global atmospheric CO_2 concentration, as well as suggesting possible mitigation strategies that align with Sustainable Development Goal 13 (Climate Action). Our study compares LSTM, Attention-LSTM, and SARIMA models for forecasting global CO_2 emissions, highlighting the better performance of SARIMA.

2. METHODOLOGY

This study employs a data-driven approach to forecast atmospheric CO_2 levels. Three different time-series models were used: Long Short-Term Memory (LSTM), Attention-based LSTM (A-LSTM), and Seasonal Autoregressive Integrated Moving Average (SARIMA). The methodology section is divided into phases, including data collection, preprocessing, model design, training and validation performance evaluation, and model comparison. Figure 1 illustrates the overall workflow of the model training and selection process.

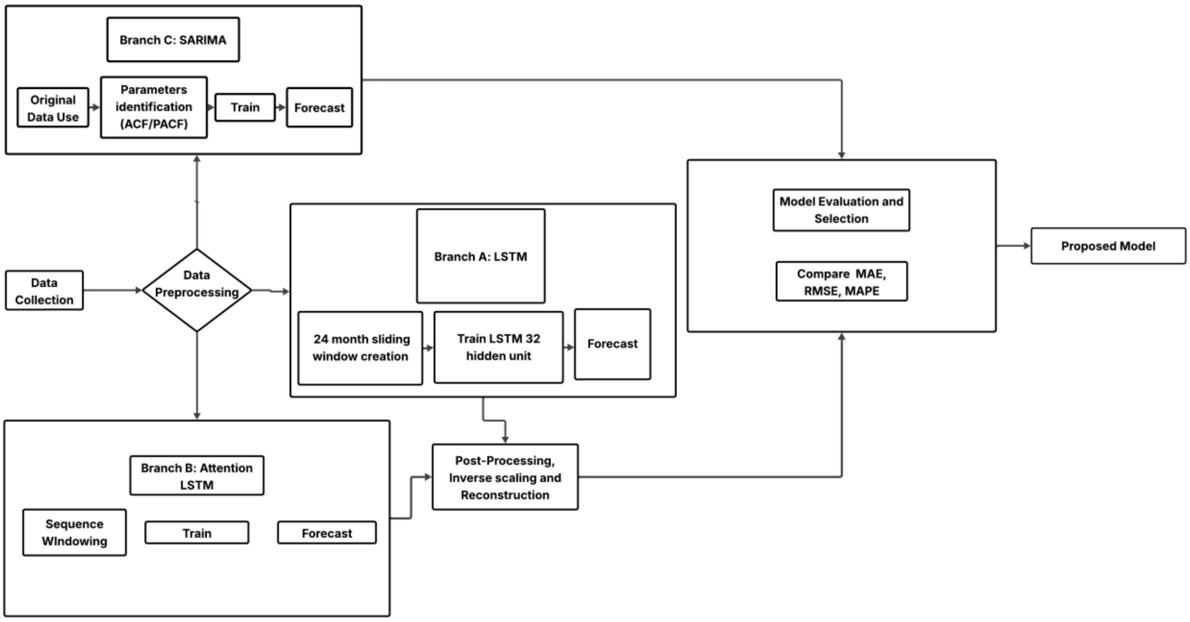

Figure 1: Workflow of model training and selection process

2.1 Data Collection

The monthly CO_2 concentration data used in this paper were collected from the IMF Macroeconomic Climate Indicators Dashboard[1] dataset, which spans a time interval from March 1958 to May 2025. The monthly CO_2 concentrations measured at Mauna Loa Observatory in Hawaii represents global estimates. The Mauna Loa data are collected at an altitude of 3,400 meters in the northern subtropics. It may not reflect the average global CO_2 concentration at the surface. The dataset contained 1,608 records when it was downloaded, with fields including Country (World), ISO 2, ISO 3, Indicator, Unit, Source, CTS Code, CTS Name, CTS Full Descriptor, Date, and Value (in ppm). The data shows a dry air mole fraction. This fraction is calculated by dividing the number of CO_2 molecules by the total number of molecules in the air after removing water vapor. The mole fraction is expressed in parts per million (ppm). Each row contains the ppm value for different months.

[1] See https://climatedata.imf.org/pages/access-data

[2] See https://climatedata.imf.org/datasets/9c3764c0efcc4c71934ab3988f219e0e/about

[3] **Source:** Dr. Pieter Tans, National Oceanic and Atmospheric Administration (NOAA). Global Monitoring Laboratory, Trends in Atmospheric Carbon Dioxide (https://gml.noaa.gov/ccgg/trends/) data and Dr. Ralph Keeling, Scripps Institution of Oceanography, Carbon Dioxide Measurements (https://scrippsco2.ucsd.edu/)

2.2 Data Preprocessing

Data preprocessing plays a vital role in ensuring the quality and reliability of the input for model training. Initially, the dataset was examined for missing values, duplicates, and inconsistent rows and columns. There were two types of values in the value column: raw ppm values and percentages. Rows with percentage values were filtered out. Among all the columns, the date and value columns were kept for the forecasting models, and the dates were converted into a datetime format and sorted in ascending order. The cleaned dataset has 807 non-null entries and two features. For the SARIMA model, we set the date as the index. The following steps were also performed: To achieve stationarity for neural models, first-order differencing was applied using (value.diff()), and the initial missing records were removed. Differenced values were normalised using Min–Max scaling to accelerate model convergence and stabilize gradients during training. Supervised learning samples were generated using a 24-month input window (input = 24), allowing models to predict subsequent CO_2 values iteratively. The time series was partitioned sequentially. The training data formed the initial segment, while the last 72 months (3 × 24) were reserved for validation to ensure chronological integrity and avoid leakage.

2.3 Model Development

2.3.1 Long Short-Term Memory (LSTM)

LSTM stands for Long Short-Term Memory and is an RNN-based deep learning model capable of learning long-term dependencies. An LSTM unit is composed of several components, including the input gate (i_t), forget gate (f_t), and output gate (O_t), as well as the previous cell state (C_{t-1}), previous output (h_{t-1}), memory cell (C_t), and layer outputh_t. They can be computed by the following equations (Faruque et al., 2022):

$$i_t = \sigma\, g(W_i . x_t + U_i h_{t-1} + b_i) \tag{1}$$
$$f_t = \sigma\, g(W_f . x_t + U_f h_{t-1} + b_f) \tag{2}$$
$$O_t = \sigma\, g(W_o . x_t + U_o h_{t-1} + b_o) \tag{3}$$
$$\widetilde{C}_t = \sigma\, tanh(W_c . x_t + U_c h_{t-1} + b_c) \tag{4}$$

Where . denotes the matrix multiplication operation, b_f , b_i , b_o, and b_c are four bias vectors, the weight matrices U_f , U_i, U_o, and U_C connect the previous output to the three gates and the memory cell. The W_f, W_i, W_o, and W_C are the weight matrices, the $\sigma g()$ represents the gate activation function, which here is a sigmoid function, and $tanh()$ is the hyperbolic tangent function, as seen in the equations above. The cell output state C_t and the layer output h_t can be determined as follows (Faruque et al., 2022):

$$C_t = (f_t \oplus C_{t-1}) + i_t \oplus \widetilde{C}_t \tag{5}$$
$$h_t = O_t \oplus tanh\,(C_t) \tag{6}$$

Where $\oplus$ denotes the element-wise matrix/vector multiplication operator. An advanced gated memory unit in LSTM eliminates the vanishing gradient problems of the vanilla RNN model (Verma et al., 2023). The key idea in LSTM is that the cell state remembers values over arbitrary time intervals, and the gates regulate the flow of information into and out of the cell (Saha & Senapati, 2020).

2.3.2 Attention-Based LSTM (A-LSTM)

To enhance the LSTM's focus on influential time steps, an attention layer was incorporated. Attention can capture the most essential input features and assign them higher weights. In time series data, the importance of different time points may be different (Abbasimehr & Paki, 2022). The attention mechanism consists of several steps, and each step is calculated in a sequential order. Initially, the attention score is calculated using equation (7), and subsequently, the weight, along with the context vector, is determined by equations (8) and (9) (Kumar et al., 2023).

$$e_{t,i} = a\,(s_{t-1}, h_i) \tag{7}$$

$$\alpha_{t,i} = softmax(e_{t,i}) \tag{8}$$

$$C_t = \sum_{i=1}^{T} \alpha_{(t,i)} h_i \tag{9}$$

Moreover, LSTM performed poorly when the input sequence exceeded 20. Therefore, the attention mechanism is integrated with the LSTM network to address the aforementioned problem and improve prediction accuracy.

2.3.3 Seasonal Autoregressive Integrated Moving Average (SARIMA)

The SARIMA model was employed as a statistical benchmark due to its robustness in handling both trend and seasonal components in time series data. Initially, the series data are checked for non-stationarity using the Augmented Dickey-Fuller (ADF) test, as SARIMA applies to such data. The p-value was found to be higher than 0.05, indicating that the time series is non-stationary with a 95% confidence level. We check if, with one-step differentiation, the time series becomes stationary (i.e., a trendless time series). This model takes two kinds of orders namely order and seasonal order (p, d, q) and (P, D, Q, s) (Sirisha et al., 2022) where p, d and q are integers greater than or equal to zero and refer to the number of autoregressive lags, order of integration and number of moving average lags respectively and P, D and Q represent the seasonal AR, differencing, and MA components, respectively (Hassan et al., 2024). The SARIMA (2, 1, 2) (1, 1, 2, 6) model was fitted using the stats model library in this study. Seasonal decomposition (Figure 2) and ACF/PACF (Figure 3) plots guided the selection of parameters.

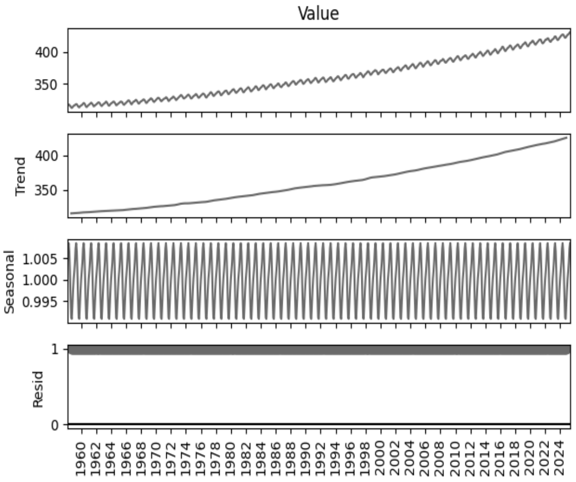

Figure 2: Seasonal decomposition of CO_2 data

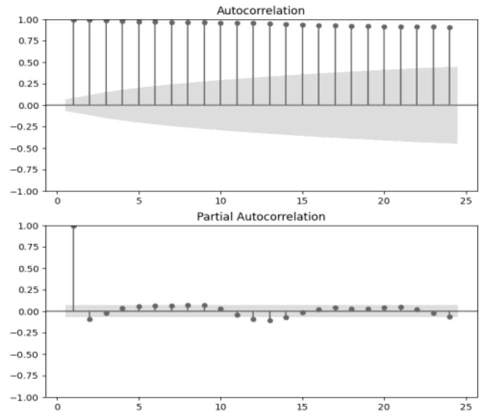

Figure 3: ACF and PACF plots

While the monthly atmospheric CO_2 data usually follow a seasonal trend each year (s = 12), our evaluation of the model showed that SARIMA model with seasonal lengths of s = 6 and s = 12 had similar forecasting accuracy, yielding almost identical MAPE, MAE and RMSE values on the validation set. Given this similarity, we decided to go with a seasonal length of s = 6 to keep things straightforward and minimize the complexity of the model. Also, choosing a shorter seasonal window enhances model simplicity and estimation stability, especially for time series with limited sample sizes, all while preserving predictive accuracy (Sirisha et al., 2022). From a policy perspective, a semi-annual seasonal structure allows for quicker short-term forecasts, helping policymakers and climate monitoring systems detect significant shifts in atmospheric CO_2 levels more swiftly, rather than waiting for a full annual cycle to play out.

2.3.4 Model Training and Validation

This section starts with data preparation and ends with forecasting for both LSTM and A-LSTM. In the middle, the training procedures were done using Adam optimizer with an initial learning rate of 0.0005, minimizing the mean squared error (MSE) between predicted and actual differenced values, 100 epochs with a batch size of 8 and verbose 1. The use of a dropout rate of 0.2 in both the LSTM and A-LSTM layers provided regularization, and no additional regularization or early stopping criteria were applied. Activation function $tanh$ was used for both LSTM and A-LSTM. After training, each model produced one-step-ahead forecasts on the validation input sequences, which were then iteratively propagated to obtain multi-step forecasts in the differenced domain.

Figures 4 and 5 show the training and validation loss curves for both LSTM and A-LSTM. It indicates that the training proceeded as expected for both models, as rapid convergence is evident from the initial epochs, and the validation stabilized after a certain number of epochs. A-LSTM showed slightly lower validation loss than LSTM, demonstrating the added benefit of the attention mechanism in enhancing prediction accuracy. The fluctuations in training loss for both LSTM and A-LSTM show some trouble in generalizing from the data. This issue frequently occurs when training deep learning models with limited temporal information.

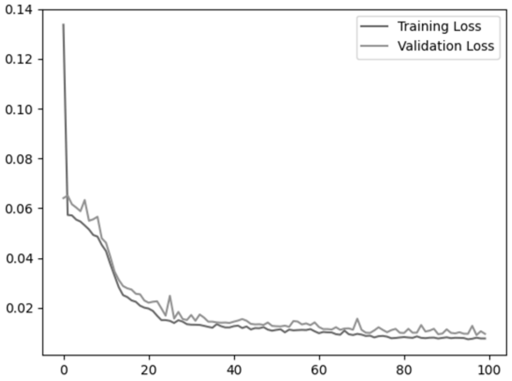

Figure 4: Loss curves of LSTM model

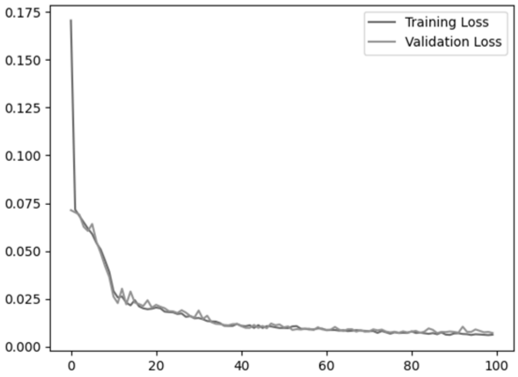

Figure 5: Loss curves of A-LSTM model

3. RESULT ANALYSIS

3.1 Quantitative Performance Evaluation

The performance of the three models, LSTM, A-LSTM, and SARIMA, was quantitatively measured using metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Table 1 summarizes the evaluation matrices for all the models.

Table 1: Evaluation Matrices

Models	MAPE	MAE	RMSE
LSTM	2.74	11.53	11.55
A-LSTM	2.43	10.25	10.27
SARIMA	0.06	0.27	0.33

The LSTM model had an MAPE of 2.74%, an MAE of 11.53, and an RMSE of 11.55. While these results demonstrate decent performance, a noticeable error is observed when compared to SARIMA, particularly in the MAE and RMSE metrics. The LSTM model successfully captured the overall trend of the data but struggled with the more minor seasonal fluctuations and precise predictions of peak and trough points. The larger error margins show this compared to SARIMA. The higher MAPE indicates that LSTM's predictions strayed more from the actual values, likely due to its struggle to fully understand the seasonal variations in the data.

The Attention-based LSTM (A-LSTM) reached a MAPE of 2.43%, a MAE of 10.25, and an RMSE of 10.27. The drop in error metrics compared to LSTM shows that the attention mechanism helped the model focus on key time steps in the input sequence. This led to better short-term predictions. The lower MAE and RMSE indicate that A-LSTM followed the underlying trends and seasonal patterns more efficiently than LSTM. However, even with these improvements, A-LSTM's performance still falls short of the SARIMA model, particularly in terms of MAE and RMSE.

The SARIMA model delivered the best results, achieving the lowest values in all metrics, a MAPE of 0.06%, MAE of 0.27, and RMSE of 0.33. This shows that SARIMA effectively captured the seasonal trend more effectively than LSTM and A-LSTM. The small MAE and RMSE further confirm that the model produced reliable predictions with minimal error. SARIMA's ability to directly model seasonal cycles and include trend differencing gave it a clear advantage over the LSTM and A-LSTM models, which learn these patterns without breaking down the seasonality.

3.2 Actual VS Prediction Graphs

Figures 6, 7, and 8 show the actual vs prediction graphs for LSTM, A-LSTM, and SARIMA, respectively, which clearly illustrate the differences in model performance. In the case of LSTM and A-LSTM, the forecasts appear to closely follow the general upward trend but deviate more significantly from the actual values during periods of sharp seasonal transitions or peaks. In contrast, SARIMA’s predictions exhibit a much tighter alignment with the actual observed CO_2 levels. The model accurately captures both the seasonal peaks and troughs, as evidenced by its significantly lower error metrics. The actual vs. predicted graph for SARIMA (Figure 8) shows minimal deviation, with forecasted values nearly identical to the actual values throughout the test period, especially during seasonal transitions.

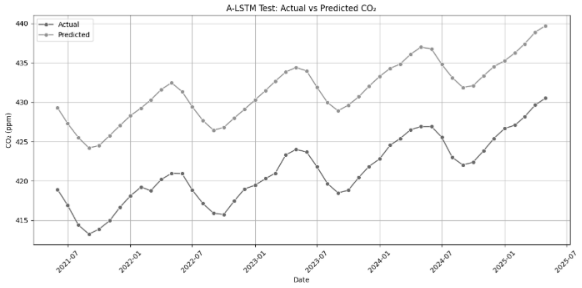

Figure 6: Actual vs predicted trend (LSTM)

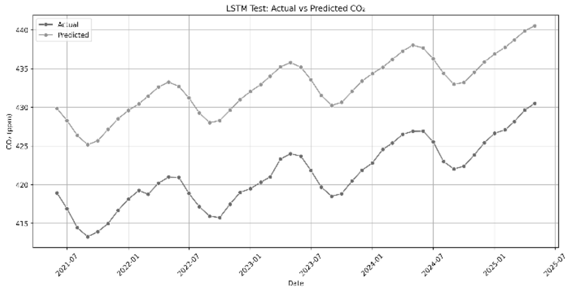

Figure 7: Actual vs predicted trend (A-LSTM)

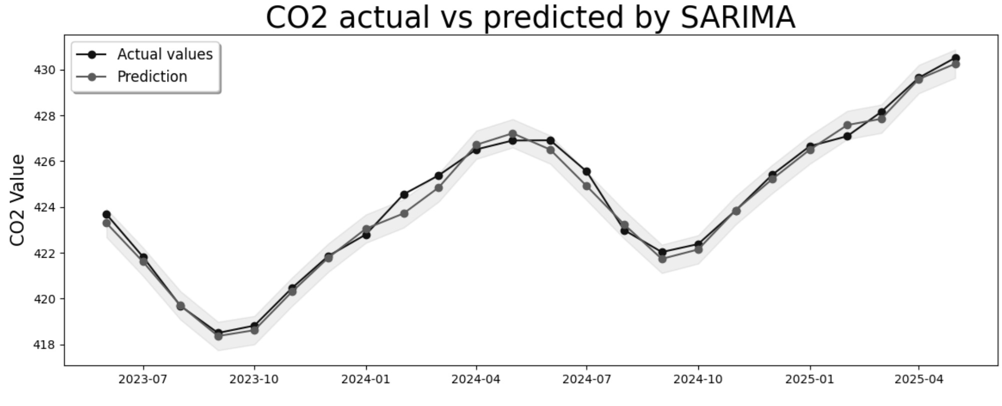

Figure 8: Actual vs predicted trend (SARIMA)

3.3 CO_2 Forecasting Using LSTM, A-LSTM, and SARIMA

Figures 9, 10 and 11 show CO_2 forecasts using LSTM, A-LSTM, and SARIMA, respectively, to further reinforce the model comparison. LSTM and A-LSTM are effective in predicting long-term trends but less effective in predicting short-term seasonal fluctuations. This is especially evident in months where CO_2 levels show sudden increases or decreases. On the other hand, SARIMA accurately tracks both the general trend and the seasonal fluctuations with minimal deviation. The seasonal decomposition and explicit handling of seasonal differencing allow SARIMA to outperform LSTM and A-LSTM in forecasting tasks where seasonality plays a dominant role.

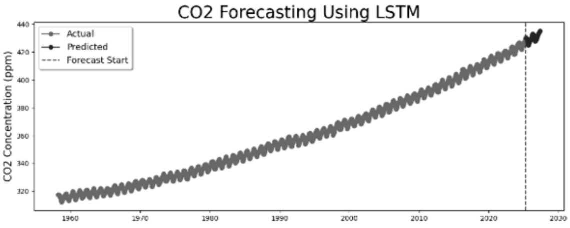

Figure 9: LSTM forecasting

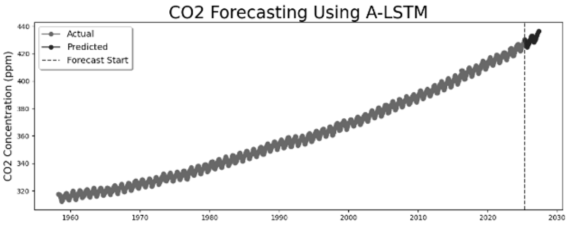

Figure 10: A-LSTM forecasting

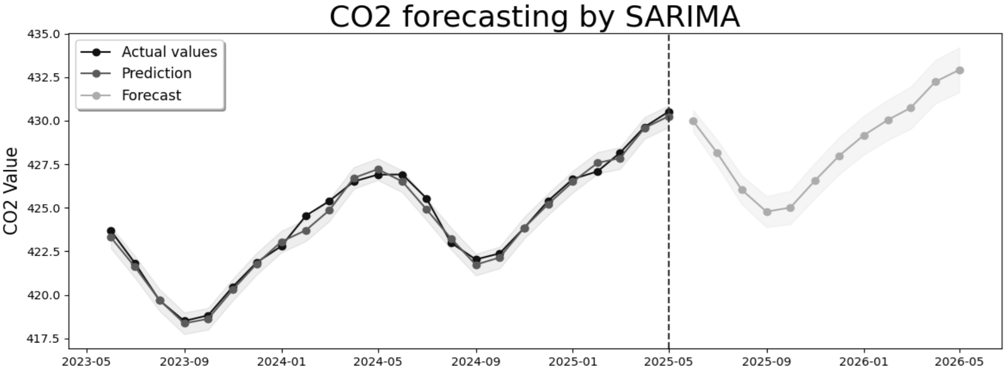

Figure 11: SARIMA forecasting

4. DISCUSSION

The comparison of LSTM, A-LSTM, and SARIMA reveals the strengths and weaknesses of each model in forecasting CO_2 concentrations. SARIMA proved to be the best model because it can effectively address seasonality and trends. This makes it perfect for the dataset, which exhibits seasonal patterns. The low MAPE, MAE, and RMSE values indicate that SARIMA works well for time series forecasting in environmental data where seasonal elements play a significant role. LSTM, as a deep learning model, showed promise but struggled to effectively capture seasonal variations. Although it followed the overall trend, the higher error metrics highlight its limitations in accurately forecasting the exact peaks and troughs in the CO_2 levels. The LSTM's inability to fully capture seasonality is likely due to its reliance on learning temporal patterns from the data without explicit seasonal decomposition. A-LSTM showed improvement over LSTM. However, even with these improvements, A-LSTM's performance did not surpass that of SARIMA, particularly in terms of MAE and RMSE. The attention mechanism made the model easier to interpret, but it did not significantly improve accuracy on this relatively simple univariate time series.

Accurate short-term forecasting of atmospheric CO_2 levels is crucial for creating early warning systems, public dashboards, and tools for climate communication. When these forecasts are integrated into real-time monitoring platforms, they can turn complex climate risks into clear, immediate signals that are easy for both the public and decision-makers to understand. Similar data-driven awareness systems have shown their effectiveness in environmental monitoring (Rafi et al., 2023), highlighting the significant potential of forecasting global CO_2 concentrations to enhance climate awareness and inspire behavioural change.

5. POSSIBLE MITIGATION STRATEGIES

The forecasting horizon from September 2025 to May 2026 (Figure 11) marks an important window for policy initiatives as an increased trend can be noticed in CO_2 concentration level during this period. So, countries are anticipated to enhance their climate action plans and mitigation strategies. By relying on short-term concentration forecasts, policymakers can make timely adjustments and be more agile in their responses, unlike with long-term projections that often involve more uncertainty (Lobus et al., 2023; Nunes, 2023).

Necessary mitigation and awareness plans should be implemented to reduce the concentration of greenhouse gases in the world's atmosphere. Addressing a projected rise in atmospheric CO_2 requires a broad, multifaceted approach. Experts note that reducing CO_2 emissions cannot be achieved through just one measure. Instead, multiple strategies must be employed simultaneously (Lobus et al., 2023). In practice, this means rapidly reducing carbon emissions in the energy and industrial sectors, enhancing energy efficiency, increasing carbon sequestration, and modifying societal behaviour. One review, for example, highlights that effective mitigation can be reached by using sustainable energy sources, improving energy efficiency, employing carbon capture and storage, and practising responsible land use (Nunes, 2023). The following can be the possible global mitigation strategies-

Renewable energy & efficiency: Transitioning all power and heat generation to zero-carbon sources (wind, solar, hydro, nuclear, green hydrogen) while upgrading efficiency in buildings, factories, and grids, as well as deploying renewables and efficiency measures, dramatically cuts CO_2 per unit of energy. (Nunes, 2023). Real-world implementations demonstrate the viability of such a transition. For instance, a techno-economic analysis reduces CO_2 emissions by 50 tons per year, offering a scalable model for integrating renewables into urban infrastructure (Rafi et al., 2025).

Clean transportation: Electrify and decarbonise transport. The widespread use of electric vehicles and mass transit, along with stricter fuel economy standards, will significantly reduce oil combustion (Nunes, 2023). (Study showed that shifting to EVs and other low-carbon transport is a key measure in cutting transportation emissions (Nunes, 2023)).

Carbon capture and storage (CCS): Developing and deploying CO_2 capture technologies at large emitters, such as power plants and cement and steel factories, is essential. Capturing CO_2 before it escapes and storing it underground or using it in industry can stop gigatons of CO_2 from entering the atmosphere. This includes improving methods, such as membrane separation, to capture approximately 90% of stack CO_2 (Nunes, 2023).

Natural carbon sinks (forests and soil): Protect, restore and expand forests and other ecosystems. Reforestation and afforestation (planting new forests) pull CO_2 out of the atmosphere while conservation agriculture and soil management lock carbon in the ground. Responsible land use practices, such as reforestation, afforestation, sustainable forestry, and conservation agriculture, are highlighted as essential, as they can sequester large amounts of carbon and prevent emissions from deforestation (Nunes, 2023).

Sustainable agriculture and diets: Modernising farming to be climate smart (precision fertilisation, methane-reducing livestock practices) and promote diets lower in carbon. Reducing meat consumption and adopting sustainable agricultural practices can significantly reduce greenhouse gas emissions (Nunes, 2023). Globally, if high-emission countries and households shift toward plant-based diets and efficient food systems, food-sector CO_2 emissions could fall substantially. (Nunes, 2023; Guan et al., 2025).

Public awareness and behavioural change: Engaging individuals and communities is essential. Education campaigns and transparent "carbon footprint" information motivate voluntary actions. The effectiveness of public-facing awareness systems is evidenced by research in related environmental domains. A study on pollution mitigation successfully deployed a system that used real-time data displays to inform the public (Rafi et al., 2023), a model that can be directly adapted for CO_2 awareness to motivate low-carbon lifestyle choices. Studies show that low-carbon lifestyle choices (using energy-saving appliances, minimizing waste, driving less, flying less, consuming less meat, etc.) can make a sizable dent in emissions when adopted widely. Indeed, a recent analysis estimates that if the top ~24% of emitting households worldwide adopt low-carbon consumption patterns, global emissions could decrease by ~10.4 gigatons CO_2 (roughly 32% of current emissions) (Guan et al., 2025). In practical terms, this means encouraging simple actions, such as taking public transit, eating a plant-rich diet, recycling, and conserving home energy, all of which have well-documented benefits for reducing CO_2 emissions.

6. CONCLUSIONS

While deep learning models, such as LSTM and A-LSTM, provide flexibility and ease of understanding, traditional models like SARIMA remain very effective for forecasting environmental time series characterised by seasonality and trends. In this study, the SARIMA model performed best, demonstrating the importance of selecting a model based on the data's characteristics. This research contributes to the growing body of knowledge on CO_2 forecasting and provides valuable insights into the strengths and limitations of various methods. The findings suggest ways to improve forecasting accuracy and emphasize the ongoing need for hybrid models and the inclusion of additional variables to enhance environmental prediction systems.

7. DECLARATION OF USE OF AI

The authors acknowledge the use of AI-based language assistance tools (including ChatGPT by OpenAI) during the preparation and revision of this manuscript. These tools were used solely to improve language clarity, organization, and readability. No AI tools were used in the research design, data collection, data analysis, model development, forecasting, or interpretation of results. All scientific content, analyses, and conclusions presented in this paper are the sole work and responsibility of the authors.

REFERENCES

Alsharkawi, A., Al-Sherqawi, E., Khandakji, K., & Al-Yaman, M. (2025). Advanced Global CO_2 Emissions Forecasting: Enhancing Accuracy and Stability Across Diverse Regions. *Sustainability*, 17(15), 6893. https://doi.org/10.3390/su17156893

Rafi, M. A. I., Sohan, M. R., Rayhan, G. J., Khairul, M. S. I., Noman, A. A., & Nadid, M. H. (2024, December). Air Pollution Prediction and Classification with a Hybrid ANN-LSTM Model in Modern Cities: A Comparative Study. In *IET Conference Proceedings CP908 (Vol. 2024, No. 30, pp. 580-585)*. Stevenage, UK: The Institution of Engineering and Technology. https://doi.org/10.1049/icp.2025.0313

Wen, T., Liu, Y., He Bai, Y., & Liu, H. (2023). Modelling and Forecasting CO_2 Emissions in China and Its Regions Using a Novel ARIMA-LSTM Model. *Heliyon*, 9(11), e21241. https://doi.org/10.1016/j.heliyon.2023.e21241

Park, M.-J., & Yang, H.-S. (2024). Comparative Study of Time Series Analysis Algorithms Suitable for Short-Term Forecasting in Implementing Demand Response Based on AMI. *Sensors*, *24*(22), 7205. https://doi.org/10.3390/s24227205

Gogeri, I., Gouda, K. C., & Sumathy, T. (2024). Modeling and Forecasting Atmospheric Carbon Dioxide Concentrations at Bengaluru City in India. *Stochastic Environmental Research and Risk Assessment*, 38, 1297–1312. https://doi.org/10.1007/s00477-023-02629-4

Aguir Bargaoui, S. (2019). Carbon Dioxide Emissions Mitigation Strategies' Performance (MPRA Paper No. 103853). University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/103853/

Martin, Will. (2000). Reducing Carbon Dioxide Emissions through Joint Implementation of Projects. Policy Research Working Paper; No. 2359. © http://hdl.handle.net/10986/19841

Kumari, S., Singh, S. K (2023). Machine Learning-Based Time Series Models for Effective CO_2 Emission Prediction in India. *Environ Sci Pollut Res* 30, 116601–116616 (2023). https://doi.org/10.1007/s11356-022-21723-8

Luo, Y. (2023). CO_2 Emission Prediction Based on Prophet, ARIMA and LSTM. *Highlights in Science, Engineering and Technology*, 76, 385-390. https://doi.org/10.54097/4k6yfr37

Rafi, M. A. I., & Sohan, M. R. (2024, June). Enhanced solar radiation prediction with machine learning: A Comprehensive Analysis of Meteorological Data Using Random Forest. In *2024, the 15th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6)*. IEEE. 10.1109/ICCCNT61001.2024.10725976

Mountzouris, C., Protopsaltis, G., & Gialelis, J. (2025). Short-Term Forecast of Indoor CO_2 Using Attention-Based LSTM: A Use Case of a Hospital in Greece. *Sensors*, 25(17), 5382. https://doi.org/10.3390/s25175382

Zhang, J. (2023). Time Series Analysis of Greenhouse Gas Emission Based on ARIMA and LSTM. *Highlights in Science, Engineering and Technology*, 76, 378-384. https://doi.org/10.54097/zy49qb44

International Monetary Fund. (2022). Macroeconomic Climate Indicators Dashboard. [Atmospheric CO_2 Concentrations], https://climatedata.imf.org/pages/access-data

Faruque, M. O., Rabby, M. A. J., Hossain, M. A., Islam, M. R., Rashid, M. M. U., & Muyeen, S. M. (2022). A Comparative Analysis to Forecast Carbon Dioxide Emissions. *Energy Reports, 8*, 8046–8060. https://doi.org/10.1016/j.egyr.2022.06.025

Verma, A., Dhankhar, H., Misra, R., Singh, T. N., & Dhakal, O. P. (2023, December). Analysis and Forecasting of Carbon Emissions in SAARC Countries using Attention-Based LSTM. In *2023 IEEE International Conference on Big Data (BigData)* (pp. 3396–3404). IEEE. https://doi.org/10.1109/BigData59044.2023.10386385

Nath Saha, B., & Senapati, A. (2020, July). Long short-term memory (LSTM) based deep learning for sentiment analysis of English and Spanish data. In the *2020 International Conference on Computational Performance Evaluation (ComPE)* (pp. 442–446). IEEE. https://doi.org/10.1109/ComPE49325.2020.9200054.

Abbasimehr, H., & Paki, R. (2022). Improving time series forecasting using LSTM and attention models. *Journal of Ambient Intelligence and Humanized Computing, 13*, 673–691. https://doi.org/10.1007/s12652-020-02761-x

Kumar, I., Tripathi, B. K., & Singh, A. (2023). Attention-based LSTM network-assisted time series forecasting models for petroleum production. *Engineering Applications of Artificial Intelligence, 123*, 106440. https://doi.org/10.1016/j.engappai.2023.106440

Sirisha, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison. *IEEE Access*, *10*, 124715-124727. https://doi.org/10.1109/ACCESS.2022.3224938

Hassan, A., Alam, M., & Faeique, A. (2023). Forecasting Monthly Inflation in Bangladesh: A Seasonal Autoregressive Moving Average (SARIMA) Approach. *Journal of Economics and Financial Analysis, 7*(2), 25-43. http://dx.doi.org/10.1991/jefa.v7i2.a61

Lobus, N. V., Knyazeva, M. A., Popova, A. F., & Kulikovskiy, M. S. (2023). Carbon Footprint Reduction and Climate Change Mitigation: A Review of the Approaches, Technologies, and Implementation Challenges. *C*, *9*(4), 120. https://doi.org/10.3390/c9040120

Nunes, L. J. R. (2023). The Rising Threat of Atmospheric CO_2: A Review on the Causes, Impacts, and Mitigation Strategies. *Environments*, *10*(4), 66. https://doi.org/10.3390/environments10040066

Rafi, M. A. I., Hasan, M. S., Hasan, M. M., Chowdhury, J. A., Sohan, M. R., Jahan, N. A., & Hossain, M. M. (2025). Techno-Economic and Environmental Analysis of Solar PV System at Sher-e-Bangla National Cricket Stadium: A Comprehensive Case Study. *IEEE Access*. 10.1109/ACCESS.2025.3553636

Rafi, M. A. I., Sohan, M. R., Jawad, A., Sourid, H. R., & Hossain, M. M. (2023, April). Sound Pollution Monitoring System and Awareness Creation in Modern Cities: A Case Study. In *2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS)* (pp. 637-642). IEEE. 10.1109/ICAECIS58353.2023.10170378

Guan, Y., Shan, Y., Hang, Y., Nie, Q., Liu, Y., & Hubacek, K. (2025). Unlocking global carbon reduction potential by embracing low-carbon lifestyles. *Nature Communications, 16*(1), Article 4599. https://doi.org/10.1038/s41467-025-59269-1

Intergovernmental Panel on Climate Change. (2021). *Climate change 2021: The physical science basis*. Contribution of Working Group I to the Sixth Assessment Report of the IPCC. Cambridge University Press. https://doi.org/10.1017/9781009157896