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# A Research Based Project on Greenhouse Gases Prediction using LSTM

***Aparna Pandey[1], Divyanshi Sharma[2], Pranjal Shrivas[3], Rishi Nirmalkar[4], S.Shubham[5]****

[1]Assistant Professor, Bhilai Institute of Technology, Raipur, Chhattisgarh, India
[2,3,4,5]Student, Bhilai Institute of Technology, Raipur, Chhattisgarh, India

A B S T R A C T

The substantial influence that greenhouse gases (GHGs) like carbon dioxide ($CO_2$), methane ($CH_4$), and nitrous oxide ($N_2O$) have on climate change and global warming has made their increasing concentrations a serious concern. Precise estimation of greenhouse gas concentrations is necessary for prompt environmental planning and policy development. Long Short-Term Memory (LSTM) networks are used in this research project's deep learning-based method to predict future concentrations of important greenhouse gasses. The capacity of LSTM, a kind of Recurrent Neural Network (RNN), to recognize long-term trends and relationships makes it especially well-suited for time-series data.The model is trained using historical atmospheric data that has been preprocessed to guarantee quality and consistency and gathered from reputable worldwide databases. To evaluate the model's prediction accuracy, performance evaluation metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are used. The experimental findings show that, in comparison to conventional statistical techniques, the LSTM model forecasts GHG levels with a high degree of precision. A scalable approach for climate trend forecasting is provided by this study, which also demonstrates the promise of sophisticated machine learning techniques in environmental data processing.

Keywords:
ARIMA – AutoRegressive Integrated Moving Average
LSTM - Long Short-Term Memory
GHG EMISSION - Greenhouse Gases Emission
RNN - Recurrent Neural Networks
SDGs – Sustainable Development Goals

## 1. Introduction

Over the last few decades, the negative effects of climate change have been more noticeable, showing up as rising sea levels, melting polar ice, more frequent extreme weather events, and rising global temperatures. The major increase in greenhouse gas (GHG) emissions, which is mostly caused by human activities like burning fossil fuels, deforestation, industrial production, and intensive agriculture, is at the core of this dilemma. Greenhouse gases, including carbon dioxide ($CO_2$), methane ($CH_4$), and nitrous oxide ($N_2O$), build up in the atmosphere and trap heat, changing the Earth's climate system in ways that are extremely dangerous for human health, ecosystems, and economy.The need for precise, timely, and trustworthy estimates of greenhouse gas emissions has never been more important given the worldwide drive to meet climate targets, such as those set forth in the Paris Agreement and theSustainable Development Goals (SDGs) of the UN. To assess the efficacy of existing policies, create mitigation plans, and prepare for upcoming changes in energy, industry, and land use, governments and environmental organizations mostly rely on emission estimates.

### *1.1. Forecasting Greenhouse Gas Emissions Using LSTM and ARIMA*

Understanding and reducing the effects of climate change depend heavily on the prediction of carbon emissions. Predicting carbon emissions accurately can help encourage the adoption of sustainable practices across industries and inform regulatory decisions. Conventional time-series models, such SARIMA and ARIMA, have been used extensively to predict carbon emissions, but they frequently have trouble with the long-term dependencies and non-linearity present in environmental data. Deep learning methods, in particular Long Short-Term Memory (LSTM) networks, have drawn a lot of interest lately due to their capacity to model intricate, non-linear relationships in time-series data and capture temporal dependencies.The use of time-series deep learning models—more especially, LSTMs—for carbon emission prediction is examined in this work. We examine how well LSTM networks handle multivariate time-series data, including variables like GDP, industrial output, energy use, and demographic characteristics. In terms of forecasting horizon and prediction accuracy, the model's performance is compared to conventional forecasting techniques. The findings show that LSTMs perform noticeably better than conventional models, offering more reliable and accurate forecasts for long-term trends in carbon emissions. The work demonstrates the promise of deep learning techniques in climate change research, providing a viable substitute for conventional techniques in the forecasting of carbon emissions and the formulation of policy.

### *1.2. Tables*

**Table 1 -Global agricultural greenhouse gas emissions.**

| PARAMETER | VALUES | EFFECT |
|---|---|---|
| Forest loss | 0.55 | Larger |
| Livestock | 0.36 | Moderate |
| Fertilizer | 0.19 | Smaller |

### *1.3. Model Development*

The goal of a research project on LSTM Model for Greenhouse Gases Prediction is to create a deep learning model that can precisely predict the concentration levels of key greenhouse gases, including nitrous oxide ($N_2O$), carbon dioxide ($CO_2$), and methane ($CH_4$). Gathering and preparing historical environmental data, including time-series records of greenhouse gas emissions, from dependable sources such as NASA or NOAA is the first step in the project. Because of its powerful capacity to identify long-term dependencies in sequential data, a specialized type of recurrent neural network (RNN) called Long Short-Term Memory (LSTM) is used. The model is appropriate for climate-related time-series forecasting since it has been taught to recognize intricate temporal patterns and trends in gas emissions across time. The architecture of the model includes dense layers for final predictions, dropout for regularization, and several LSTM layers. Performance measures like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are used to assess the model after it has been trained. Future patterns in greenhouse gas levels can be analyzed by visualizing the final forecasts. In addition to demonstrating the use of deep learning in environmental sciences, this research aids in the formulation of climate policy by offering forecasts of future atmospheric conditions.

### *1.4. Time-Series Forecasting of Greenhouse Gas Emissions Using Deep Learning*

The use of deep learning models—more especially, Long Short-Term Memory (LSTM) networks—for time-series CO2 emissions forecasting is investigated in this work. The model forecasts future emission patterns more accurately than conventional techniques by utilizing past emissions data in conjunction with socioeconomic and environmental factors. The findings demonstrate how well deep learning techniques capture intricate temporal relationships and nonlinear patterns, providing insightful information to help policymakers manage and reduce greenhouse gas emissions.

### *1.5. Existing Methodology*

Several techniques have been employed over time to predict GHG emissions. Conventional models such as VAR, ARIMA, and linear regression have been widely used. Although linear regression implies linearity and ignores complicated dynamics, it does link emissions to variables like GDP or energyIn certain situations, machine learning models that handle nonlinearities better—such as SVR, decision trees, and random forests—offer increased accuracy. However, they need to handle time-based information manually because they are not inherently able to understand temporal sequences.use. ARIMA works well for short-term univariate time series, but it has trouble with long-term trends and nonstationary data. For multivariate data, VAR builds on ARIMA, although it still requires a lot of fine-tuning and assumes linear correlations.Artificial Neural Networks (ANNs), particularly feedforward networks, have been employed to address issue; but, until lag elements are introduced, they are unable to retain information about previous inputs. Sequence modeling was made possible by recurrent neural networks (RNNs), however they have vanishing gradients. Long Short-Term Memory (LSTM) networks, which use memory cells and gating mechanisms to capture long-term dependencies, tackle this problem. In terms of accuracy and robustness, LSTMs have outperformed both traditional and machine learning models in the forecasting of greenhouse gas emissions.

### *1.6. Proposed Methodology*

The suggested approach for LSTM network-based GHG emission prediction is a multi-phase, structured procedure. The first step is gathering historical emissions data ($CO_2$, $CH_4$, and $N_2O$) and associated indicators from reputable sources, such as energy consumption, GDP, industrial activity, and population. In order to preprocess this data, missing values are handled, scales are normalized, and time steps are aligned. Key variables are then identified by feature engineering, which may involve dimensionality reduction and the use of lagged features and correlation analysis. With a dense output layer for predictions and dropout layers to lessen overfitting, an LSTM model is constructed to capture long-term temporal patterns.The model is trained using the Adam optimizer with MSE loss, and the data is divided into training, validation, and testing segments. Through experimentation, hyperparameters are adjusted, and performance is assessed using R2, RMSE, and MAE metrics in comparison to models such as linear regression and ARIMA. Following validation, the model predicts both short- and long-term emissions, and scenario analysis is optional for evaluating the effects of policies. Tools like Flask or Streamlits can be used to visualize results, giving decision-makers useful information.

## 2. Mathmatical Equations

Each LSTM unit consists of **four main components**:

- Forget gate ftf_tft
- Input gate iti_tit
- Cell state CtC_tCt
- Output gate oto_tot

(a) Forget Gate:ft=σ(Wf·[ht−1,xt]+bf)
(b) Input Gate: it=σ(Wi·[ht−1,xt]+bi)
(c) Output Gate: ot=σ(Wo·[ht−1,xt]+bo)
(d)Hidden State (Output):ht=ot∗tanh(Ct)

## 3. Future Scope

Climate science and policymaking could be greatly advanced by using LSTM-based models for greenhouse gas (GHG) prediction. The model can be improved by adding more environmental variables like temperature, rates of deforestation, energy consumption, and industrial activity since it can recognize intricate patterns and long-term correlations in time-series data. The model can forecast in almost real-time thanks to connection with IoT-based environmental sensors and access to real-time satellite data, which makes it extremely useful for proactive climate policies and early warning systems.Furthermore, by providing data-driven insights into emission trends, extending the model to multi-country or worldwide datasets can support international climate negotiations. Another possible avenue for improving prediction accuracy and interpretability is the use of hybrid deep learning models (e.g., combining LSTM with CNN or attention mechanisms). In the end, these prediction tools can help develop more sustainable plans, monitor the advancement of climate targets, and assist international endeavors such as the Paris Agreement.

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