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Global Warming: A study of erratic fluctuations in land and oceanic temperature as influenced by heightening industrial activity and population growth

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"The earth is warming; it's warming because of human activity, and the impact is bad and will get much worse. We have every reason to believe that at some point the impact will be catastrophic." - Bill Gates

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ABSTRACT: *Tackling the global climate crisis is a daunting task. Excessive greenhouse gas emissions lead to rising temperatures and sea levels, stratospheric ozone depletion and a greater occurrence of intense, sporadic natural disasters. In order to commence the development of remedial technologies to subdue the adverse effects of global warming, it is essential to understand the range of anthropogenic and industrial activities that cause global land and oceanic temperatures to fluctuate beyond their expected statistical range. The following paper employs a myriad of machine learning algorithms in the development of deep neural networks (DNNs) that are used to forecast land and oceanic temperatures. Data input during the model's training process, (covering an overall sample period of 28 years from 1990 - 2018), consists of sectoral carbon emission values of the top 20 contributors to the climate crisis worldwide—as well as additional correlated factors, such as population growth rate and gross domestic product (GDP) growth per capita, incorporated to create a comprehensive and versatile predictive tool. Results indicate high predictive accuracy of the model, with a low mean square error (MSE) of 0.208 and a high coefficient of determination (r^2) of 98.7%, implying a high degree of explainability regarding variations in predictions.*

KEYWORDS: Global warming, Land and oceanic temperatues, Greenhouse gas emissions, Artificial Intelligence, Deep learning, Deep Neural Networks (DNNs), Artificial Neural Network (ANN).

INTRODUCTION

Rising global temperatures, a phenomenon constituent of the prominent global warming crisis, is undeniably one of the most prevalent global issues facing modern society. In order to combat this issue, a comprehensive prediction model should be made available, in order to facilitate an understanding of the crisis at large. This can be achieved using a range of machine learning algorithms that may be employed to train deep neural networks (DNNs), in order to create a basis for forecasting land and oceanic temperatures globally—a method which is explored in this research paper.

Within the last century, the world has experienced an unforeseen amount of growth in its population, an occurrence which has imposed an inordinate amount of pressure on the Earth's scarce reserves of natural resources [15]. Considerable technological advancements coupled with the advent of industrialisation and urbanisation of communities around the world have facilitated the exponential increase in global demand, as cost-efficient, streamlined manufacturing concurrently perpetuates a shift in consumer behaviour towards a trend of rapid overconsumption—at a speed that inhibits the natural regeneration period of salient natural resources, such that insatiable demand from growing economies worldwide continue to incentivise commercial and capitalist agents to further harvest rapidly depleting, scarce resources [20].

This phenomenon often culminates in mass deforestation, which not only destroys the natural habitats of native fauna, but causes radical disruptions in local ecosystems that result in catastrophic imbalances within earth's natural biomes, (a balance which, if otherwise achieved, would foster the cyclical regeneration of resources overtime) [14]. Furthermore, deforestation and rampant commercial activity, (including global trade), entails the emission of carbon dioxide (CO_2), hydrofluorocarbons and other harmful greenhouse gases into the atmosphere, which perpetuates all aspects of the climate crisis. Thus, intemperate anthropogenic activity and changes in land use and forestry have undeniably rippling implications on global warming, notably the incumbent rise in land and oceanic temperatures worldwide [3].

In order to forecast these temperatures accurately, the current study considered a range of environmental factors, including percentage of forest area that constitutes countrys 'total land mass, to account for the effects of deforestation on the response variable. The study further examined the distinct, non-cumulative sectors of industrial activity that contribute to the emission of carbon dioxide (CO_2) into the atmosphere, such as energy generation and transportation. The top 20 emitting countries, which collectively contribute over 78% of global GHG emissions [8], were examined as representative of the global climate crisis. Key indicators, derived from the World Bank of Open Data, were used alongside fluctuations in economic activity and population growth, as determinants of the emission output of particular countries and economic sectors.

This research report begins with an investigation into the factors that affect global warming, as an assessment of the necessary variables to be input into the predictive model. An in-depth literature review is further conducted to determine the ideal methodology for the development of an accurate deep neural network. The various hyperparameters for the final model are then disclosed, before the results, (including scaled-importance graphs and a sample of the predictions), are presented. The report further provides a range of graphical representations portraying the accuracy of the model, that support the evaluation of the obtained results. Logical conclusions are drawn based on this information.

Hypothesis

The author hypothesises that the developed model will allocate considerable weightage to the forest area factor, as representative of the detrimental effects of deforestation on global warming, as well as high scaled importance to energy generation and fuel combustion amongst the sub-sectors that comprise aggregate carbon dioxide emissions, as indicative of increased industrial activity and heightened consumer demand. Forecasted land and oceanic temperature values are hypothesised to fluctuate minutely, yet with distinct variation in each year, as a result of increasingly volatile climatic conditions.

Background

Climate change is largely the product of the 'greenhouse effect', a phenomenon which is composite of the properties of greenhouse gases in relation to atmospheric conditions. Increasing concentrations of such gases—namely carbon dioxide (CO_2), methane gas (CH_4) and nitrous oxide (N_2O), amongst other artificial chemicals—absorb transmitted solar energy and re-radiate its heat towards Earth's surface, resulting in increases in land and oceanic temperatures [11]. Human activity accounts for the majority of this greenhouse gas emission output, with over 47552.14 million metric tons of CO_2 equivalent gases ($MtCO_2e$) expelled in 2018.

Global emission output can largely be attributed to three multifarious sectors: energy, agriculture and industrial processes [8]. Energy consumption accounts for over 73% of global GHG emissions. This sector comprises electricity and heat generation, transportation, manufacturing and construction, bunker fuel usage, fugitive emission output and other fuel consumption. Fugitive emissions, or fluorinated gas emissions, arise from industrial gas production processes, electrical component and appliance manufacturing, as well as the the extraction and refinement of aluminium and magnesium. These processes emit high concentrations of heat-trapping chemicals, (possessing a warming effect of up to 23000 times greater than that of carbon dioxide), such as hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF6), thus contributing significantly towards the net greenhouse gas emission output [12]. Additionally, the release of chlorofluorocarbons (CFCs), decomposes ozone molecules in the upper atmosphere, exposing the Earth to the sun's ultraviolet radiation that stimulates the release of volatile organic compounds (VOCs) from plants, plant litter and soils, further constituting harmful emissions from these greenhouse gases. Bunker fuel emissions, however, refer to the pollution caused by fuels used aboard ships, notably amassed fleets of cargo vessels transporting manufactured goods. Bunker fuels are a key disaggregated contributor to total emissions, owing to their composition of largely hydrocarbon molecule chains.

Further, agricultural subsectors of which include emissions generated by the cultivation of livestock and crops, are cited as the second greatest contributor to climate change (12%). Primary activities, including cattle belching and fertiliser usage, emit methane gas (CH_4) and nitrous oxide (N_2O) respectively, representing the greatest proportion of agriculturally affiliated emissions, at upto 65%. Another crucial contributor to climate change are industrial processes, a sector which has expanded by 174% since 1990, the fastest growing source of greenhouse gas emissions worldwide [11]. The increased manufacture and usage of appliances such as air conditioning and refrigerators are responsible for this uptick, as large quantities of potent hydrofluorocarbons are expelled as a product of industrial activity.

Whilst growing demand and increased commercial activity is largely responsible for the burning of fossil fuels within a selection of the aforementioned sectors, they also promote mass deforestation, which further contributes to GHG emissions. During the process of photosynthesis, trees absorb harmful carbon dioxide gas from the atmosphere and emit oxygen, however, they also perform the opposite process in a phenomenon known as 'respiration'. Within large forests, the volume of carbon dioxide absorbed exceeds that which is expelled during respiration—with any excess carbon stored in tree trunks, roots and soil in a process called sequestration—creating a positive net environmental effect [21]. However, when masses of trees are cut down during deforestation, these underground reserves of carbon are released into the atmosphere, perpetuating the establishment of a 'heat-trapping blanket 'constituting Earth's ozone layer, that causes volatility in land and oceanic temperatures globally.

LITERATURE REVIEW

Scholars worldwide have adopted a range of methodologies to forecast global temperatures, as a baseline for climate change. A selection of these studies are examined below, in order to inform the procedure of this experiment.

Climate change prediction using artificial neural network

One such method, as implemented in a study entitled 'Climate change prediction using artificial neural network 'conducted by Zahraa Maamoon Mohammed Amin et al. entails the integration of a multitude of environmental factors, such as air temperature, land temperature and relative humidity, exclusively—which the study ascertained as determinants for climatic conditions affecting the key response variable—as inputs into the neural network, which consisted of weather data from 22 cities in a constrained, local geographical region. However, despite limited consideration of contributing factors to the global climate crisis, such as greenhouse gas (GHG) emissions, the procured model predicted air temperature with high accuracy, using a feed-forward backpropagation training method backed by linear regression.

Prediction of Land Surface Temperature Using Artificial Neural Network in Conjunction with Geoinformatics Technology Within Sun City Jodhpur (Rajasthan), India
Another study, conducted by Avinash Kumar Ranjan et al in 2018, involved the development of an artificial neural network in order to predict land surface temperature within Jodhpur, Rajasthan. The study adopted land surface temperature (LST) as the response variable, using converted discrete data obtained from pixellated geoinformatic imagery to approximate temperature inputs into the ANN model. Researchers notably assessed parameters, regression (R)—to signify a positive correlation between the target and veritable output values—as well as mean square error (MSE) to assess the extent of the model's predictive accuracy. The use of linear regression algorithms resulted in a high correlation coefficient of 0.94 and low MSE, thus indicating a strong association between real and forecasted temperatures.

Hybrid Multivariate Statistical and Neural Network Model to Predict Greenhouse Gas Emissions
A differing technique was adopted by Miranda et al. in a 2021 study entitled 'Hybrid Multivariate Statistical and Neural Network Model to Predict Greenhouse Gas Emissions', concerning the prediction of greenhouse gas emissions in tropical reservoirs. The developed model, which coupled both statistical and ANN models to facilitate classification and prediction, respectively, used factor analysis to condense input variables to evoke greater prediction accuracy. The examined works assess primarily industry specific variables (singular, sectoral-centric analysis), with data pertaining to a constricted sample size for limited countries and skewed time periods; the aforementioned study exclusively addressing a confined selection from the entire range of contributing gases to global warming.

4.4 Prediction of sea surface temperatures using deep learning neural networks
An alternate approach was adopted by Partha Pratim Sarkar et al in a study titled 'Prediction of sea surface temperatures using deep learning neural networks 'that aimed to predict exclusively sea surface temperatures (SST) using deep neural networks. Researchers uniquely experimented with a variety of architectures, including non-autoregressive neural network with exogenous output (NARX) under differing training algorithms (Bayesian and Levenberg–Marquardt), alongside the traditional feed-forward back-propagation model, in order to assert the optimal configuration for the model, which avoids 'overfitting 'to the input data and critically, facilitates generalisation for wider applications of the developed model.

Theoretical: Neural Networks and Deep Learning
Neural Networks (NNs) are computational models that mimic the processing capabilities of the human brain by deploying a range of mathematical and AI algorithms that process data through a configuration of interconnected 'neurons', or nodes, that resemble the functioning of biological nerve cells. Neural networks are effective tools for complex, non-linear statistical data modelling, as they consist of input, hidden and output layers, that contain several processing elements that receive inputs and deliver outputs based on a predefined activation function [13].

Activation functions form the basis for computation in neural networks, by asserting the relevance of particular data inputs in obtaining a desirable output, thus determining how the data is processed through the model's hidden layers.

Amongst the most prevalent classifications of neural networks are Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs), or Multi-Layer Perceptrons (MLPs); whilst both models employ similar basic function, a key distinction between the two is that MLPs contain more than one hidden layer between the input and output layer, meaning that data is processed through multiple intermediary layers, which subject data to the model's activation function.

The rectifier activation function (applied to the study's deep learning model), unlike sigmoidal and hyperbolic tangent functions, does not completely saturate; when processed, values, if > 0, remain as the original input, whilst all else values (< 0) snap to 0. Therefore, this function is able to accurately comprehend complex relationships within the data and compute variable importances for factor analysis. The model was trained using a deep learning algorithm with backpropagation, in conjunction with an adaptive learning rate algorithm (ADADELTA) [6].

In order to train deep neural networks using stochastic gradient descent with backpropagation of errors, a nonlinear function, which appears and behaves like a linear function is required. This particular characteristic of the ReLU activation function allows increasingly complex relationships in the data to be comprehensively understood and consequently generate accurate predictions.

Experimental Design
In order to predict variances in global temperature, raw data was procured from the Berkley Earth database of the response variable 'land and oceanic temperatures', for a sample period of 23 years (1990 - 2013), using the latest publicly available records. Predictions of the response variable made by the current study will therefore commence from 2014, constituting the 'future 'years to be forecasted for, as no data for these years have been published.

Related data was obtained from the World Bank and World Resources Institute databases covering a sample period of 28 years (1990 - 2018) to account for long term variations in factor inputs. To develop an accurate, representative model, key contributors to climate change were input into the deep neural network framework. Further demographic statistics and economic metrics, namely population growth rate and gross domestic product (GDP) growth per capita, respectively, were factored into the model, as both inputs demonstrated a distinct relationship and direct contribution to forecasted temperature values.

Table 1 features the variables examined and their units of measurement, alongside the variable type as regressors input into the DNN.

Table 1 Data and variable definition

Variable	**Unit**	**Variable Type**
Year	Time (YYYY)	Time
Country	Factor	Enum
Global Land and Oceanic Temperature	Degrees Celsius (ºC)	Numeric
Forest area (% of land area)	Percentage (%)	Numeric
CO_2 emissions (metric tons per capita) by sector: 1. Agriculture 2. Building 3. Electricity/Heat 4. Energy 5. Fugitive Emissions 6. Industrial Processes 7. Manufacturing/Construction 8. Other Fuel Combustion 9. Transportation 10. Waste	$MtCO_2e$	Numeric
GDP Growth Rate (annual %)	Percentage (%)	Numeric
Population Growth Rate (annual %)	Percentage (%)	Numeric

METHOD

Preliminary Research - The initial stage of the research project entailed a thorough investigation into the current conditions of the global climate crisis by examining the impact of various environmental factors on the study's response variable, land and oceanic temperature. This process facilitated the assertion of associated factors to be input into the developed model, in order to produce an array of accurate forecasts that are representative of socio-economic environments as they exist in prevalent communities around the world. Insights gained from secondary sources, such as research papers, journals and government databases, informed the aforementioned conclusions—whilst a general investigation into

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machine learning softwares formed the basis for the creation and training of the deep neural network.

Data Collection - In order to process the complex data, obtained from a range of databases including the World Bank of Data and Berkeley Earth, which comprised of several different data types, (such as time, enumerated and numerical), raw data files were first procured and then appropriately formatted into country specific records, that associated unique data, such as sector specific CO_2 emission output figures, with recurring data values, such as population growth per capita and GDP growth rate, which were applicable across all records pertaining to a particular year. As the study examined a wide range of global emitters, consisting of countries with varying populations and economic outputs, feature engineering techniques were implemented, (for instance, in the process of converting total population figures to annual population growth rates) to ensure that variances in such parameters did not skew factor analysis (scaled importance of inputs) or predictive accuracy of the model.

1. Developing the Neural Network -

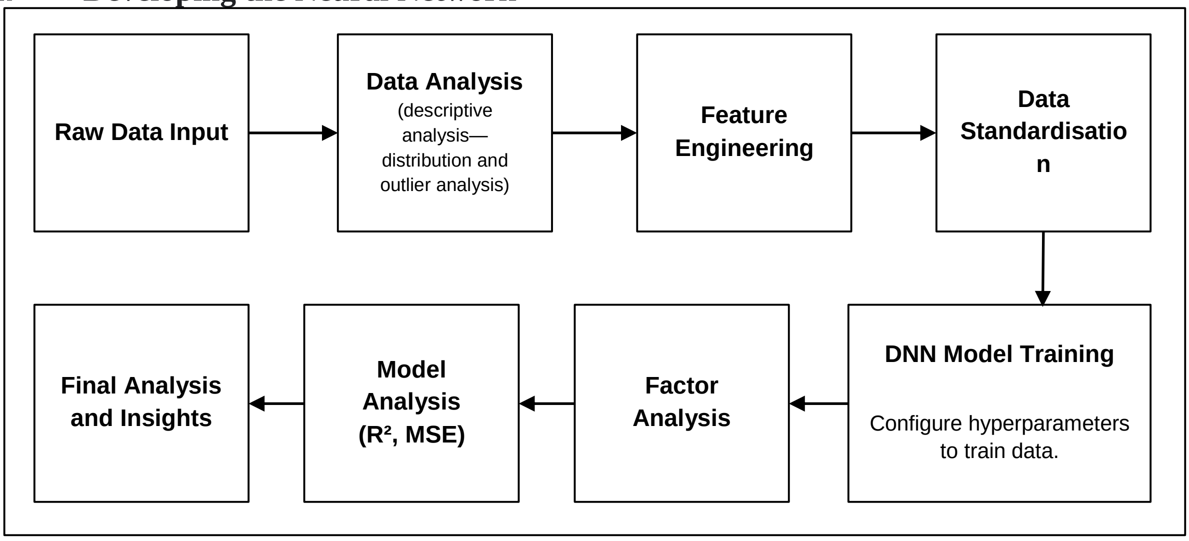

Fig. 1 Framework of the study

The creation, training and testing of the neural network was executed using R, a statistical software and data analysis tool, within the RStudio integrated development environment (IDE). During the development process, the data was first parsed, processed through a configuration of hyperparameters that were adjusted throughout the experimentation process and then computed by a range of machine learning algorithms, via H2O—a comprehensive artificial intelligence (AI) platform that facilitates the deployment of multiple supervised and unsupervised AI algorithms as modelling techniques.

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RESULTS AND DISCUSSION

Hyperparameters, including epochs(35)/iterations and hidden layer sizes, were optimised within the H2O program in order to generate a model with the highest r^2 value (minimising the cost function), possessing a high degree of explainability regarding variations in the data. The model training process (number of epochs) persisted until the cost function (evaluated in this case by RMSE/r2) was minimised using a stopping metric—as reflected in the exemplar scoring history from the experiment.

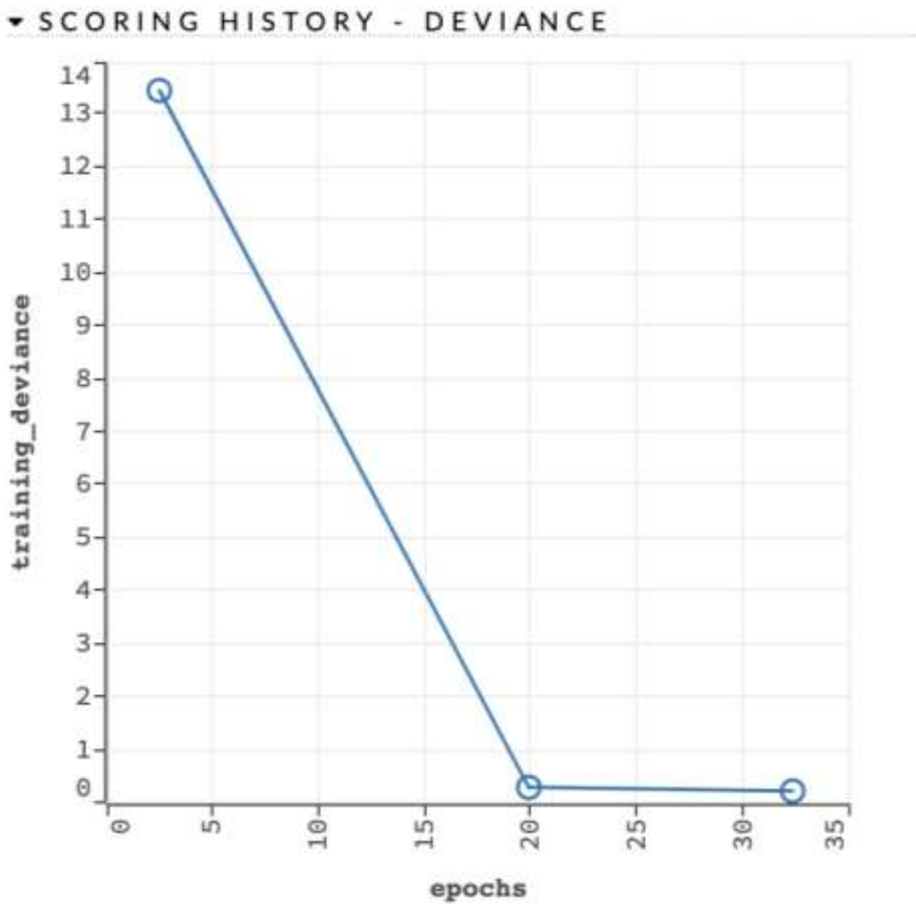

Fig. 2 Scoring history for training data

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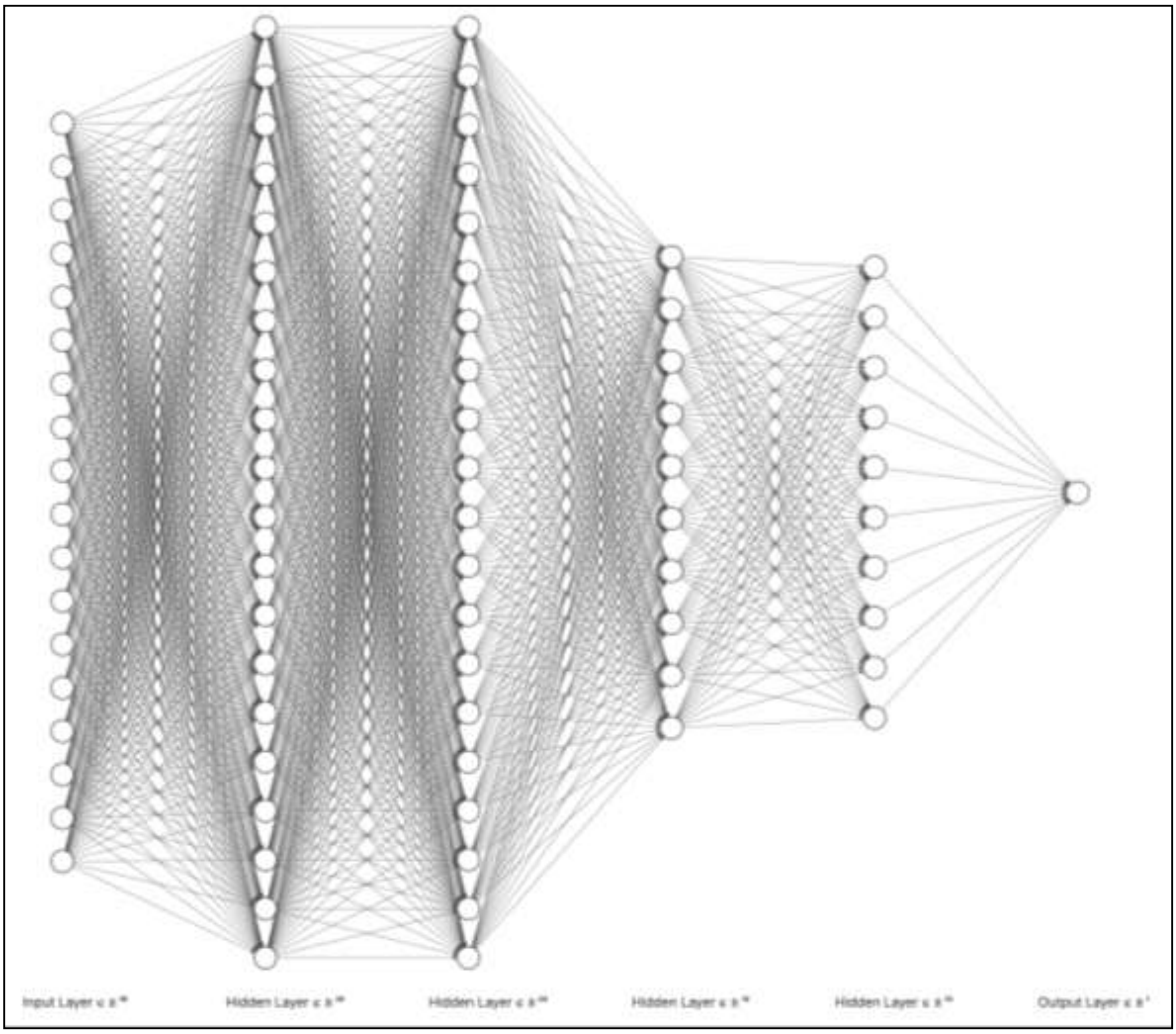

Fig. 3 Architecture of the deep neural network

Note: intermediary layers are scaled down by a factor of 10 for representation purposes.

As depicted in the architecture of the deep neural network (Fig. 3), the study employed eighteen variables at the input layer, of numeric, time and enumerated type (Table 1). Variables were subject to processing through the hidden layers using the Rectifier (ReLU) activation function, without dropout. Configuration of the hidden layer magnitudes (200, 200, 100, 100) were derived and optimised for accuracy, during the experimentation process, using a deep learning grid search. The model, once developed, postulated the variable importance of inputs and a basis for the prediction of land and oceanic temperatures.

The factor analysis, (as depicted in Fig. 4) produced a scaled variable importance of the regressors assessed, in relation to the response variable. The DNN indicates that countries India, Indonesia and Canada are of considerable weightage when predicting changes in land

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and oceanic temperature globally. As observed by examining the raw data input, these countries were not only notable for their high volume of carbon emissions, but their extreme temperatures (high and low), as observed within the raw data, which exceeded the mean land and oceanic temperature of other countries.

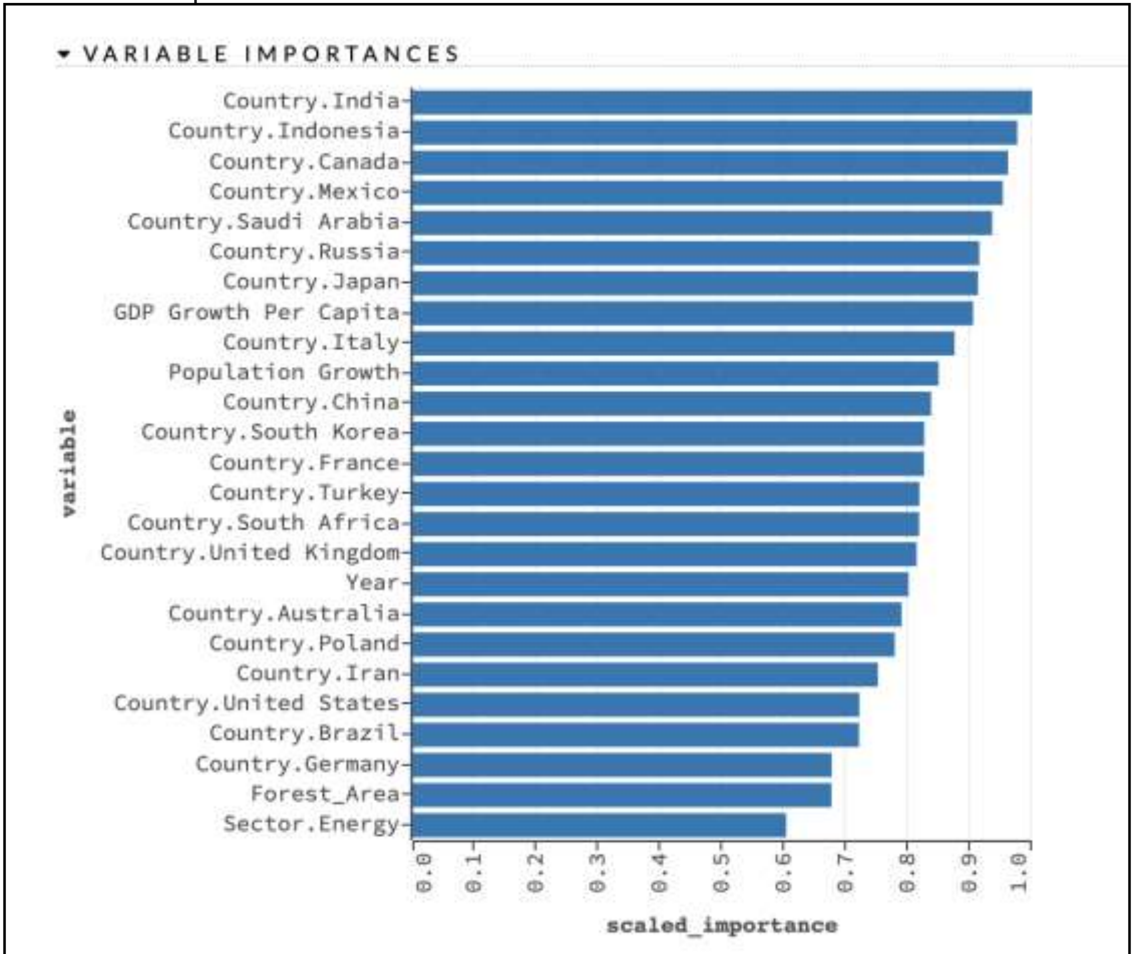

Fig. 4 Primary factor analysis (including countries)

Assessed metrics for determining model accuracy include mean square error (MSE), of which this model generated a promising 0.208 and coefficient of determination (r^2) of 99.7%, meaning that any variations in the data of the studies' range of dependent variables can be explained by the response (independent) variable. As in machine learning, the r^2 metric defines how well the model fits the data, the optimal r^2 values lie in the range of 95-100%—hence the developed model's high r^2 signifies a high degree of accuracy.

However, primitive trials indicated excessive reliance of the model on factor inputs, such as countries—thus overshadowing the impact of salient environmental factors, such as percentage of land reserved for forestry and agricultural purposes, as well as socio-economic parameters, such as GDP growth per capita and increases in population. In order to combat this, the study developed a parallel factor analysis in accordance with the proposed deep neural network

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employed for temperature predictions, (using constant hyperparameters), that critically excluded arbitrary 'factor', enum variables which labelled data records, in favour of an evaluation of supplementary inputs (Fig. 5).

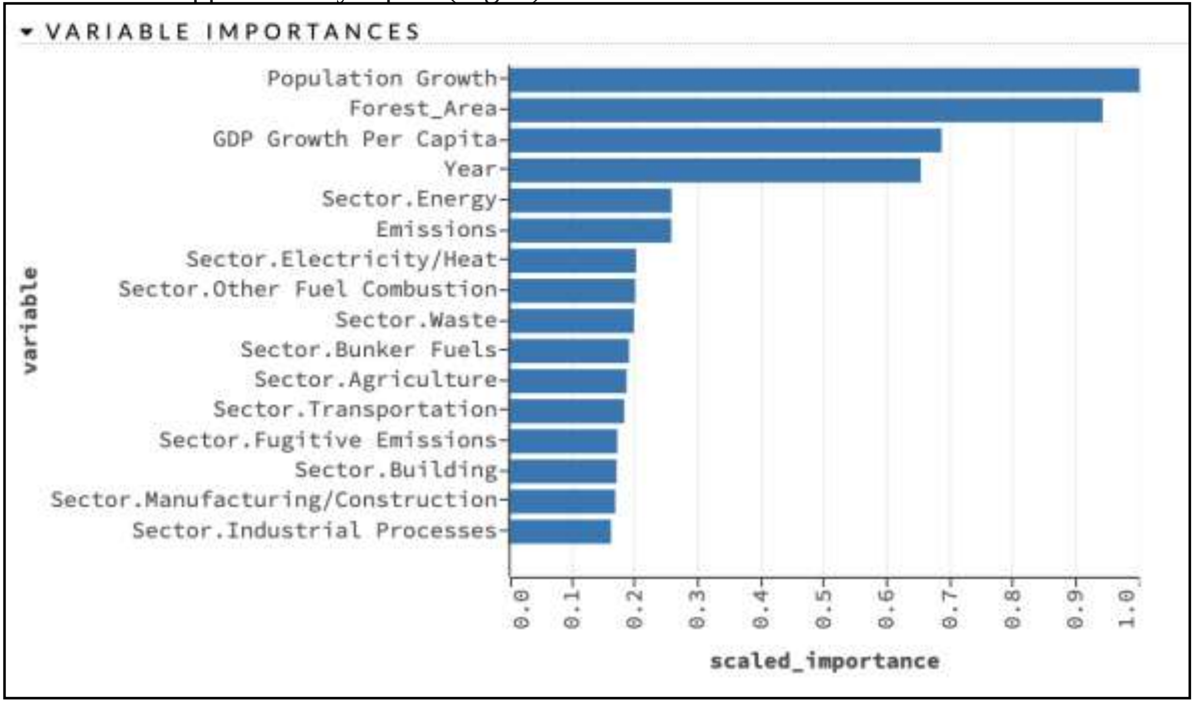

Fig. 5 Factor Analysis of Numeric Factors

This secondary, more focussed factor analysis highlights the significance of expanding populations to climate change, with both population growth and GDP growth per capita ranked within the top three contributing factors. Results critically indicate the importance of changes in forest area, (ranked as the second highest important variable overall), to increases in land and oceanic temperature, as hypothesised.

This analysis further postulates the relative contribution of each subdivision of carbon emissions to the model, thus indicating that energy, electricity/heat and other fuel combustion, bear the greatest significance, whilst industrial processes, fugitive emissions, and construction are of a lower relative importance to predicting the study's response variable, as supported by the theoretical research conducted.

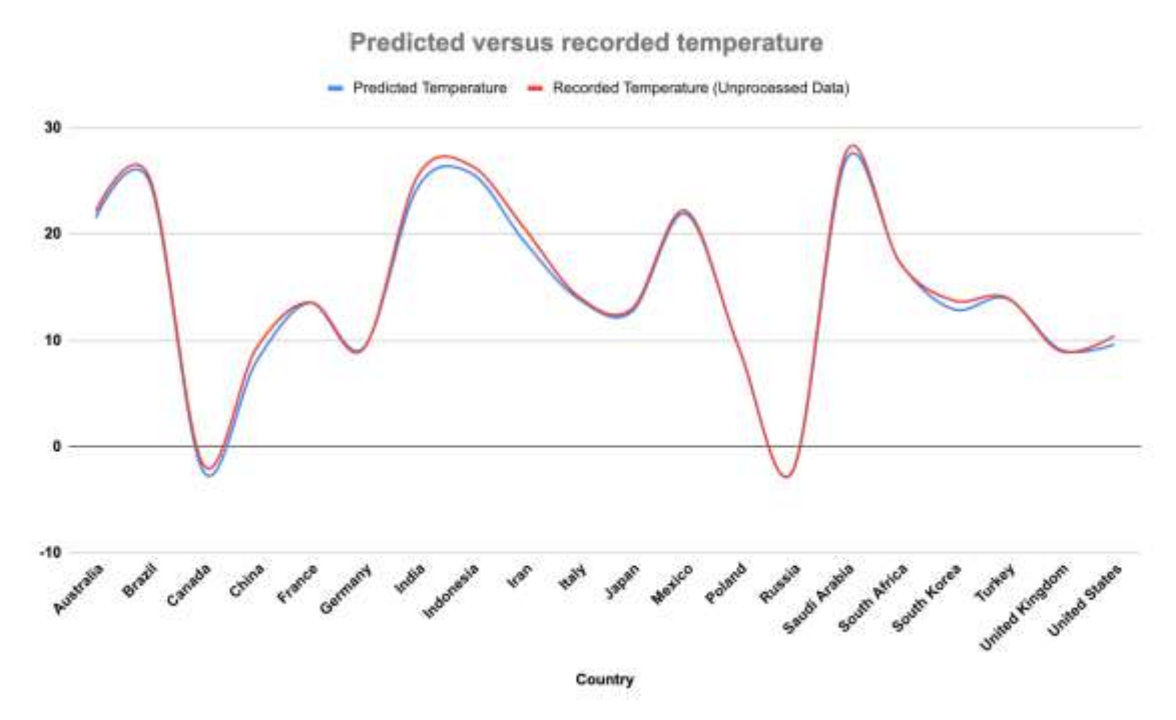

Fig. 6 Predicted versus recorded temperature values

In order to comprehensively evaluate the accuracy of the developed model, predicted temperature values were compared with historical, recorded temperature data. As evidenced in Fig. 6, the DNN predicts temperature with great precision. In most instances of diversion from veritable values, minor underestimation occurs in countries with generally volatile land and oceanic temperatures, which demonstrated a high degree of variability, as per historical data which was input during the training phase.

The developed DNN model, possessing the same degree of accuracy as presented in Fig. 5, was used to predict theoretical temperature output values for a sample period of 2014 - 2018, (beyond the response variable's publicly available data, uptil 2013), to facilitate validation and assessment of accuracy. Table 2 depicts the forecasted values, in ºC, rounded to two decimal places, alongside historical temperature data (2009 - 2013), which were input during the development of the DNN. As per the model, considering demographic and economic variances, average land and oceanic temperature amongst chosen countries are forecast to fluctuate in tenths between 14 - 15ºC. Despite the rather minor nominal fluctuations in temperatures within the time period, these minute variances accelerate the process of climate change significantly, resulting in severe observable impacts that cause ice caps to melt and lead to disruptions in established global weather patterns.

Table 2 Historical versus predicted temperatures

	Temperature Data (°C) Source: Berkeley Earth Database					**Deep Learning Model Prediction Sample - Temperature (°C)**				
Country/Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Australia	22.69	22.08	21.77	22.02	22.14	21.49	21.56	21.63	21.59	21.80
Brazil	25.60	25.81	25.43	25.72	25.35	24.33	23.32	23.00	24.41	24.36
Canada	-4.14	-1.89	-3.56	-3.18	-1.64	-1.9	-2.99	-2.86	-0.94	-1.86
China	7.81	7.55	7.36	7.08	9.3	8.18	8.24	8.24	8.17	8.16
France	13.94	13.12	14.48	13.71	13.58	13.31	13.45	13.31	13.24	13.31
Germany	9.36	8.01	9.82	9.23	9.24	9.2	9.09	9.02	9.35	9.38
India	25.15	25.05	24.42	24.64	25.41	24.53	24.39	24.19	24.04	23.94
Indonesia	26.46	26.54	26.2	26.32	26.47	25.74	25.72	25.70	25.67	25.64
Iran	19.11	20.09	18.92	18.96	20.54	20.49	20.76	20.88	20.67	20.11
Italy	14.05	13.32	14.17	14.08	14.17	13.38	13.86	13.15	13.40	13.76
Japan	12.93	13.22	12.74	12.57	12.96	12.63	12.87	13.06	13.19	12.95
Mexico	21.55	20.85	21.60	21.65	22.22	21.97	21.86	21.96	21.92	21.75
Poland	8.65	7.62	8.95	8.54	9.26	9.03	8.80	9.04	9.10	9.13
Russia	-4.61	-4.52	-3.4	-3.9	-2.26	-0.81	0.06	0.25	-0.24	-0.19
Saudi Arabia	26.83	27.53	26.64	26.99	27.74	26.76	26.53	26.82	26.62	26.17
South Africa	17.89	18.30	17.55	17.85	17.33	17.48	17.56	17.11	17.15	17.27
South Korea	12.95	12.64	12.36	12.39	13.76	12.53	12.67	12.56	13.13	12.57
Turkey	12.81	14.28	11.91	12.85	14.03	12.79	13.20	12.49	13.87	12.54
UK	9.45	8.39	9.91	9.04	9.00	8.77	8.47	9.01	8.54	8.62
United States	9.14	9.51	9.55	10.26	10.43	9.67	9.66	9.66	9.64	9.66
Average	14.38	14.38	14.34	14.34	14.95	14.48	14.45	14.61	14.83	14.45

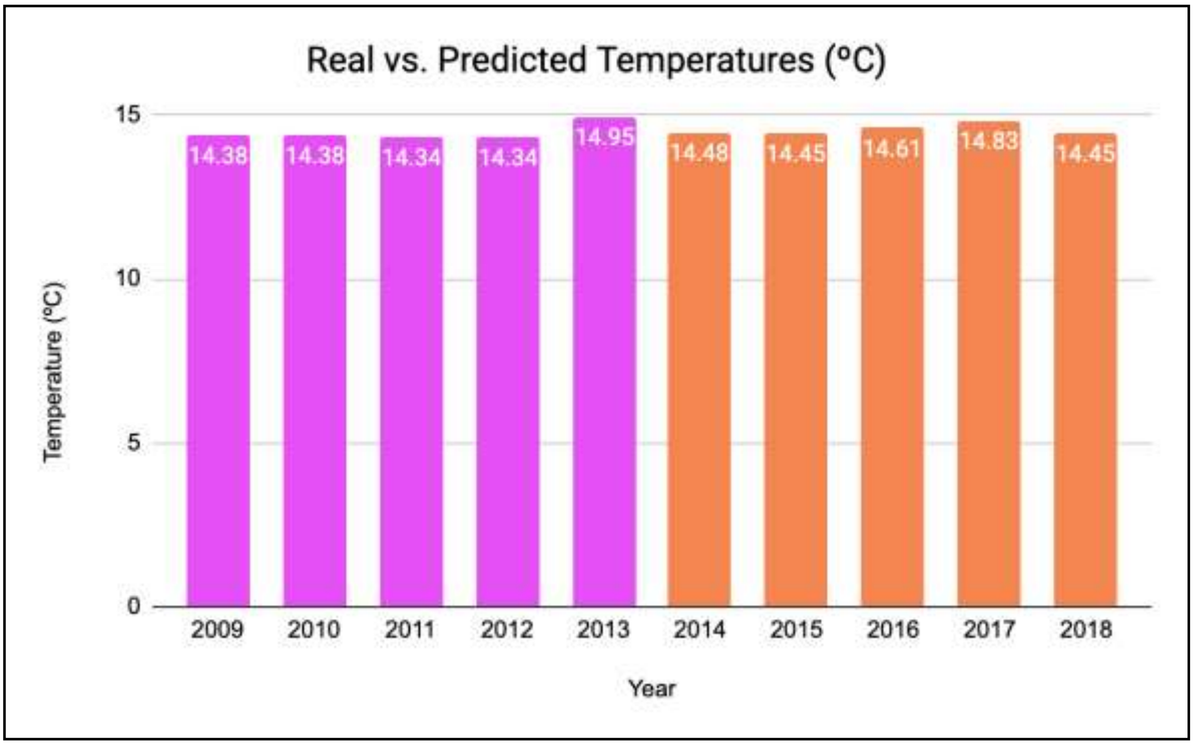

Fig. 7 Historical land and oceanic temperatures (pink) versus predicted temperature trajectories (orange) in ºC.

CONCLUSION

Rampant anthropogenic activity, instigated by growing populations, increasingly robust economies and heightened consumer demand, have perpetuated the global climate crisis. The deterioration of Earth's ozone layer in particular, is largely the product of greenhouse gas emissions, via a range of varying effects. Most notably, the presence of high volumes of greenhouse gases in the atmosphere lead to increased absorption and retention of infrared energy, which is re-emitted onto Earth's surface, leading to critical fluctuations in land and oceanic temperatures.

In order to subdue the adverse effects of global warming, humanity requires a fundamental understanding of the progression of climate change at its current rate of anthropogenic activity. Thus, the deployment of precise deep neural networks as a basis for the prediction of future environmental metrics, such as global temperatures, is critical in the process of implementing remedial technologies that can be used to curtail these effects, whilst accounting for rapidly evolving living standards and economic welfare.

Therefore, as indicated by the developed model and corroborated by external research, global mitigation initiatives should be directed towards reducing CO_2 emissions from the electricity/heat sector and the generation of energy, as well as increasing forest area, in consideration of the long term regeneration of salient natural resources. This notion aligns with the author's hypothesis denoting the significance of the energy sector towards perpetuating global warming, as well as the observable impacts of deforestation.

The developed deep learning model is robust in its predictive accuracy, as evidenced by the high r^2 and low MSE, whilst accounting for economic and demographic factors, alongside industrial phenomena, such as rising rates of deforestation. However, the model considers carbon dioxide emissions exclusively and does not account for the smaller constituent gases that comprise all greenhouse gas emissions, and future studies should incorporate this data to create a more detailed assessment of total emissions and how they may be affected by the concurrent changes in industrial processes and development of remedial technologies to the ever-evolving, eminent climate crisis.

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