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RESEARCH ARTICLE

FORECASTING GREENHOUSE GAS EMISSIONS FROM AGRICULTURAL SECTORS

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Abstract –Agriculture is one of the economic sectors that has both a direct and indirect effect on climate change, contributing to greenhouse gas (GG) emissions. This emission is created by the putrification of biomass and dry plants deposits and burning of crop leftovers. The cropped soils generate more than half of the earth's anthropogenetic N_2O fluxes, stock and discharge the organic carbon as CO_2, and can produce as well as consumeCH_4. The agricultural soils can be both emitters and sinks of GG. The sources and sinks of each of these GG varies, and each is affected differently by agronomic management. The Kyoto Protocol's architecture accounts for the interplay that occurs between the stratospheric ozone layer, solar ultraviolet (UV) rays, and climate change. In this research, the high temporal and spatial variability of farming emit the GG from the soil that need to analyse and forecast the climatic changes by using deep convolutional neural network (CNN) with Random Forest Classifier (RFC) named as CNN-RFC. The prediction is performed using humidity of air, soil texture and temperature of the atmosphere. The performance metrics is obtained from the values of root-mean-squared-error (RMSE):2.104, 13.231 and 4.128, mean-absolute-error (MAE):1.053, 10.032 and 3.653, Pearson: 0.325, 0.138 and 0.357, R^2 coefficient:0.432, 0.473 and 0.432 and standard deviation (SD):5.463, 10.587 and 3.463 for $CO_2, CH_4 and\ N_2O$ respectively.

Keywords *–Greenhouse gas (GG) emissions, Climate changes, Convolutional neural network-Random Forest classifier (CNN-RFC).*

1. INTRODUCTION

This Ozone is technically a greenhouse gas, however it is beneficial and destructive depending on where it is present in the earth's atmosphere. Ozone is present at higher altitudes in the atmosphere, known as the stratosphere, where it forms a barrier that blocks ultraviolet (UV) rays from reaching the surface of the earth, which is harmful to plant and animal life. The advantage of stratospheric ozone predominates its contribution to global warming and greenhouse effect [1,2]. The lower altitude of the atmosphere is troposphere that is harmful to the human health. The Kyoto protocol is an international agreement that was extended by the UNFCCC (united nations framework convention on climate change and commits developed nations and economies in transitions are limiting and reducing GHG emissions in accordance with agreed specific targets and it is based on the broad facts that are,

- Global warming is serious issue and will gradually destroy the world if left unchecked.
- The major source of climate change is anthropogenic CO_2 emission into the atmosphere.

This practice was adopted on December 11, 1997, in Kyoto, Japan, and took result on February 16, 2005 [4]. This treaty, which presently has 192 signature countries, lays a responsibility on industrialised countries to restrict energy consumption that have substantially led to the current high level of GHG in the environment. This emission of GHGs interacting with the atmosphere that leads to ozone layer depletion and the major GG are $CO_2, CH_4 and\ N_2O$. In 2021, approximately 1.5 billion tonnes of GG emitted in worldwide. The anthropogenic activities include cultivation, mineral extraction, petroleum and gas production and consumption, biomass fuels, and urban wastes are all have boosted methane levels in the atmosphere [7]. This suggests that, the prompt action is made in the above-mentioned sectors emission of CH_4 will continue to rise in future. The energy consumption sector is the main source of CH_4 emissions into the environment [11], which includes mining activities, natural gas and oil systems, as well as wireless combustion systems. Approximately 570 tons of CH_4 was emitted from these sources. The other sources of emissions include agricultural activities and waste management, which add roughly 245 tons of methane in the environment. CH_4 is a GG with an estimated global warming as 27–35 times more than CO_2 over the last 50 years, thus it ranks as the second most anthropogenic emission of GHG into the atmosphere [13]. The primary sources of CO_2 emissions are biofuels, solid waste, trees, and timber products, moreover that, deforestation and soil degradation release carbon dioxide into the atmosphere. N_2O is emitted by farming and manufacturing industries, as well as fossil fuel and burning of solid wastes. These excess emissions of GHG results in global warming and create changes in the weather conditions as shown in fig.1.

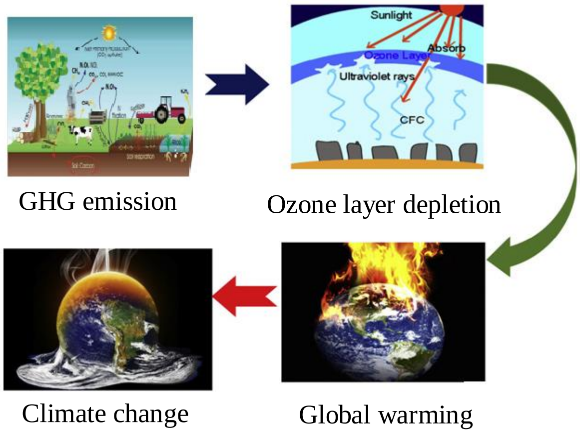


Figure.1: Climate changing due to emission of GG

CO_2 and further heat-trapping gases rising into the stratosphere and spreading out like a blanket around the earth like a layer. These blankets heat the Earth's surface while shielding it from the cold air above it. The blanket has become uncomfortably thick as the concentrations of heat-trapping gasses have increased. The earth's crust warms because it is now enveloped in a thicker blanket, which heats the layer and traps more heat in the lower atmosphere [17]. The blanket also blocks the heat transferring from the troposphere to the stratospheric, causing the earth's atmosphere to cool. On the other side, heat-trapping gases help to lower the temperatures that induce ozone depletion in the environment. At lower atmospheric levels, greenhouse gases retain heat and contribute to surface warming, whereas at higher altitudes they hinder thermal transfer upwards. Depletion of ozone in the stratosphere causes a cooling effect, which promotes ozone loss. Normally, ozone absorbs UV light and emits heat into the atmosphere. When ozone concentrations fall, less heat is created, which leads to increased cooling in the lower stratosphere. This cooling increases ozone depletion, particularly in the polar stratosphere.

Nowadays CNN serves as a vital part in demonstrating outstanding behaviour in certain fields. In this study a deep CNN with the RFC (CNN-RFC) were used to forecast the variations in weather due to the emission of GG in the atmosphere. CNN is used to predict the emission of GHG and classify through RF classifier and forecast the climatic changes in temperature variations. The remainder of the paper is divided into five sections. Section 2 provides a review of related literature. Section 3 describes the suggested framework for climate change prediction using CNN and RF classifiers. Section 4 describes the experimental findings and their analysis. Finally, Section 5 summarizes the study and identifies prospective areas for further development and investigation.

2. LITERATURE SURVEY

In recent days several deep learning (DL) techniques were introduced by the researchers mainly to detecting the climatic changes due to emission of GHG from the agricultural soils. In 2021 Awais Shakoor., *etal.*,[1] had conducted a meta-analysis study analyse the effect of GG from the agricultural sectors. Agricultural areas had a significant effect on the carbon and nitrogen cycles on the earth, that results in emission of GHG due to their huge area and meticulous management procedures. As a result of this meta-analysis, a knowledge gap was discovered regarding the effects of animal dung, region of weather, and soil physical features on GHG omissions from rural soils. This meta-analysis was performed on the usage of various forms of animal dung in agricultural soils can be beneficial for standardising and verifying machine-based models and also solving the information gaps about the emission of GHG that are resulting from the cultivated fields, lack of experimental studies and needed with optimum manure production rate to estimate the GHG emission.

In 2021 Baglaeva., *et al.*,[2] had developed non-linear autoregressive neural network model to forecast the GG. The dynamic variations in the content of GG for short-term forecast. The cause-and-effect links between rising the average temperatures and the concentrations of GG in the atmosphere are still being determined. The accuracy predicted by this model is high and the correlation coefficient between the predicted and observed GG were near 0.9 for 24 hours. Philippe.R., *et al.*,[3] had developed a country-specific (Tier-II) methodology according to the main framework proposed by IPCC in 1997 to estimate the emission of N_2O from agricultural fields of Canada.In this studya function relating the regional fertilizer-induced emission factor (EFreg) to determine the annual emission factors (EFeco) using the available field experimental data. The emission of N_2O from the fine-texture soils were estimated at over 50% than coarse-textured soils and 40% during some climatic changes.

In 2021Rakhmatova., *et al.*,[4] had proposed a hybrid model that combines artificial neural network and wavelet transform to predict methane intensity in hourly time series. This model works on the meteorological attributes obtained from the Belyy island. It improves the consistency rate of predict the dynamic changes in methane concentration. Leila Merabti., *et al.*, [5] had introduced a study that is applicable for two gadgets In varied weather circumstances, the two-stage solar vapour cooler and solar liquid desiccant cooler are tested, and several farming applications are evaluated due to emissions of GG. In such areas, ordinary circulation and shade are insufficient to maintain the greenhouse temperature at the correct set point, requiring the use of further cooling.

In 2020 Shakoor., *et al.*, [6] put forward a potential feedback model to climate forcing from biogeochemical translation of GHG emissions from the terrestrial to the atmosphere. This method examines anthropogenic GHG emission sources, microbial community responses to the variation in weather conditions, ability to influencing climatic conditions, and prevention options using various cultivation management systems and microbial populations.

In 2021 Pranali.K and Vrushali.Y [7] had designed a feed foward neural network to analysis and predict the emission of GG in the atmosphere. This network employs a sequential neural network in Keras to predict CO_2 and CH_4 from onion crops at open and holly farms.

This model hyper tuned with 3, 4 and 5 layers with different epochs; the model prediction accuracy is measured by RMSE, MSE and R-square as a coefficient of correlation. The model shows a strong prediction response for GHG emission with the onion crop as a main influencing attribute.

In 2020, Riham and Bassim [8] suggested a fuzzy logic-based method for calculating methane emissions from big municipal solid waste landfills. Because landfill gas generation involves multiple unknown and interconnected processes, properly estimating methane output is frequently difficult for landfill operators. The created model used seven input parameters and performed well, with increased prediction accuracy. However, the reliability of the fuzzy logic model is heavily reliant on the quality and availability of input data, which can restrict its efficacy when adequate data is not available.

In 2021 Sara.K., *et al.*,[9] had made an examine to detect the climatic changes using a machine learning (ML) technique. In this study the investigation was performed between the emission of GG and climatic changes in North-east Africa based on essential climate variables. By choosing a suitable method will aid in climate alteration and prevention, as well as determining the level of GHGs and their related concentrations should be maintained in order to prevent climate-related disasters and crises. The performance of Head-CNN was good and the RSME value obtained is 5.378. From this study, different ML and DL techniques were used to obtain the better predicted results. In the proposed framework, a deep convolutional neural network along with the RFC termed CNN-RFC model to anticipate and analyze the climatic variations owing to the production of GG such as CO_2, CH_4, and N_2O with improved accuracy in Fig 2.

3. PROPOSED METHODOLOGY

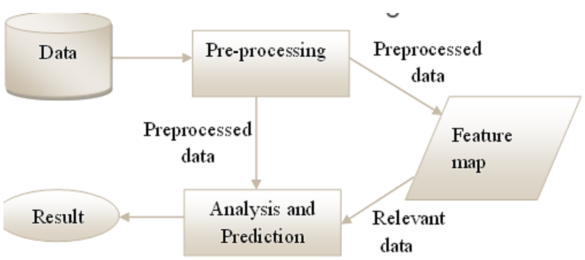


Figure.2: Structure of Proposed system

3.1 Data acquisition

The data used for analysing the emission of GG changes over a time, as the emission levels are progressively increasing in million tonnes in every year and it is treated as a time series, and make subsequent predictions. A diversity of DL models has[10] been used for examination and predicting the emission of GHG in farming sector. In this study the soil and seasonal data was collected from the farm weekly twice in the duration of 1 year from January 2020 to December 2020. The soil parameters are temperature, texture, moisture, type, NPK (nitrogen, phosphorus, potassium) values and pH values have to be examined. The climatic parameters [11] are pressure, temperature, humidity and wind speed have to be examined and the GG such as CO_2, CH_4 and N_2O are taken for this analysis.

3.2 Convolutional neural network-Random Forest classifier (CNN-RFC)

CNNs are popular DL models for classification and prediction applications. [12]They can automatically learn significant aspects from data while doing classification, resulting in higher accuracy, especially when dealing with huge datasets. CNNs are ideally suited for modeling and forecasting climate change patterns because of their capacity to capture complicated and nonlinear interactions, which are common among environmental variables. Deep neural network (DNN) with high initial values typically leads to poor threshold values. On the other hand, the low initial values result in shallow gradients in later levels by restricting the utility of tuning networks with several hidden layers (HL). [13] To address this issue, we used a residual learning technique to properly train the model. In this method, the first layer learns basic patterns and low-level representations from the input data, while successive layers extract increasingly complicated and abstract features based on the previous layers' outputs. [14] The network is gradually optimized using backpropagation, with all parameters fine-tuned across layers. This training procedure, however, can be computationally expensive when dealing with large-scale inputs and highly nonlinear data. Furthermore, the learning performance of lower hidden layers is frequently slower than that of deeper levels, particularly in networks with numerous hidden layers. [15] Despite these challenges, deep learning models excel in feature extraction because their architectures can capture rich and hierarchical representations of complex data.

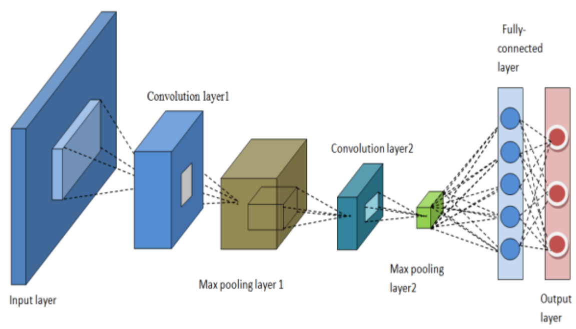


Figure.3: Architecture of CNN

Figure 3 shows the CNN model's architecture, in which the input layer receives time-series data containing all input variables. [16] The architecture aims to reduce computational complexity by removing high-cost functions. In the network, each layer processes information from the previous layer. Neurons learn simple patterns and features from input data via local receptive fields, which are then merged in deeper layers to generate more meaningful representations.[17] The outputs produced by groups of neurons are arranged into feature maps, with each feature map focused on a certain aspect of the input. Neurons inside separate feature maps detect distinct features from each element of the input data by analyzing local areas and storing their activations at matching feature map coordinates.[18] This approach allows the network to efficiently learn geographical and temporal patterns from the data. A feature map is a collection of neurons that perform the same operation at different points along the input sequence. Multiple feature maps are often incorporated in a convolutional layer, allowing the network to learn a wide range of features from data. [19] Each convolutional layer has numerous convolution kernels (filters) that discover important patterns in the input. During processing, incoming data is processed through these kernels, which use convolution to build feature representations. [20] In the case of one-dimensional data, the convolution operation moves the kernel along the input sequence and calculates feature values that capture important local patterns and relationships in the data. [21] The process for performing one-dimensional convolution is detailed below.

$$x_j^L = \sum_{i=1}^{n} x_j^{L-1} * k_j^L + b_j^L \tag{1}$$

where x_j^{L-1}defines the i-th feature map of the layer L-1,x_j^L denotes the j-th feature map of the layer L, k_j^Ldenotes the j-th convolution kernel, b_j^L represents the bias, In the convolution [22] process, the symbol (*) represents the convolution operation, and n represents the total number of input feature maps. After a feature is discovered, its relative placement in relation to other features takes precedence over its specific position inside the input. [23] To incorporate nonlinearity and boost learning capability, the Rectified Linear Unit (ReLU) activation function is used to the normalized outputs of each layer. [24] The ReLU function changes the input by keeping positive values while suppressing negative values, improving the network's capacity to learn complicated patterns from the data.

$$f(x_j^L) = \max\{0, x_j^L\} \tag{2}$$

With a given size filter, the CNN detects variants in the sequential variations of the input data over time.[25] Feature maps are used to characterize distinct parts of data. The following layer does local averaging, known as pooling, and downsampling to reduce the identification of the feature map as well as the intensity of possible shifts and output changes. [26] This approach can lead to the deletion of vital information, and the max-pooling process is characterized as,

$$P_L^{L+1}(j) = max_{(j-1)w<t<jw}\{Q_i^L(t)\} \tag{3}$$

Where $P_L^{L+1}(j)$ represents the value acquired after max-pooling process of the j-th operating state of the i-th feature map, $Q_i^L(t)$ represents the t-th neuron in the i-th feature map of layer L, [27] whereas wd determines the breadth of the pooling region. The feature maps are coupled to an FC layer, which records each feature for many inputs and outputs. The model's accuracy is governed by the suitable weight and bias settings.[28] The RFC is supervised learning model for categorization and it is derived as,

$$R(x) = 1 - \sum_{a=1}^{b} (f_a)^2 \tag{4}$$

where f_a refers to the frequency of the label at node a and b is the number of the unique labels. [29] The entropy is defined as,

$$R(x) = \sum_{a=1}^{b} -\log(f_a) \tag{5}$$

The pooled output is passed to the RFC, which classifies and recognizes the normalized features of the given output. It uses bagging or bootstrap aggregation for classification to accurate prediction[30]. It takes the input as feature sampling and row sampling with replacement. The hyperparameter allows choosing the number of decision trees (i.e., Base learners) involves in classification and it gives the results based on the probability of majority voting. [31] It collects votes from various base learners to determine the final test result. It has low bias and volatility, resulting in the best and most accurate results.

4. RESULTS AND DISCUSSIONS

The experimental setting for this paper was constructed using MATLAB 2019b, a DL toolkit. In this outcome study, datasets were utilized to predict weather variations caused by GHG emissions from agricultural sectors.

4.1 Performance analysis

The proposed model's competence is evaluated using RMSE, MAE, Pearson standard deviation and R^2 coefficients. Pearson and R^2 coefficients vary from -1 to 1, showing whether the variables are positively or negatively related. The MAE is derived as follows:

$$MAE(x, x') = \frac{1}{n} \sum_{i=1}^{n} |x'_i - x_i| \tag{6}$$

$$RMSE(x, x') = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x'_i - x_i)^2} \tag{7}$$

where x'_i and y_i are represent as predicted value,x_i is represent as observed value, the mean of predicted values y_i,n be the no. of data, and pearson correlation coefficientμ respectively. The standard deviation is derived as,

$$R(x, x') = \frac{n\sum_{i=1}^{n} x\prime_i x_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x\prime_i}{\sqrt{n\sum_{i=1}^{n} x^2{}_i (\sum_{i=1}^{n} x_i)^2} \sqrt{n\sum_{i=1}^{n} x\prime^2{}_i - (\sum_{i=1}^{n} x\prime_i)^2}} \tag{8}$$

$$SD(x, x') = \frac{1}{n} \sum_{i=1}^{n} (y_i - \mu)^2 \tag{9}$$

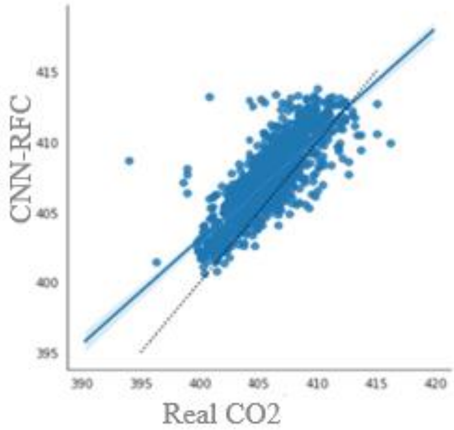
where x'_i and y_i are represent as predicted value, x_i is represent as observed value, the mean of predict values y_i, n be the no. of data, and μ denotes the pearson correlation coefficient. The Index of Agreement (IOA) is a normalized statistical metric that measures the degree of agreement between observed and anticipated values to determine model prediction accuracy. Its values vary from 0 to 1, with 1 representing full agreement and 0 indicating a lack of agreement. A higher IOA number indicates the model's greater prediction performance. The mathematical expression for computing IOA is provided below.

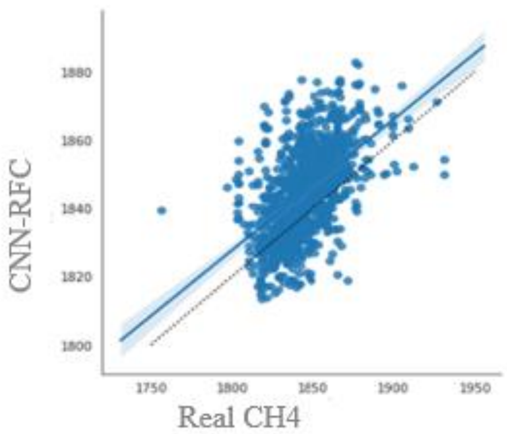
$$IOA = \frac{\sum(o-p)^2}{\sum(abs(o-m\prime) + abs(p-m'))^2} \tag{10}$$

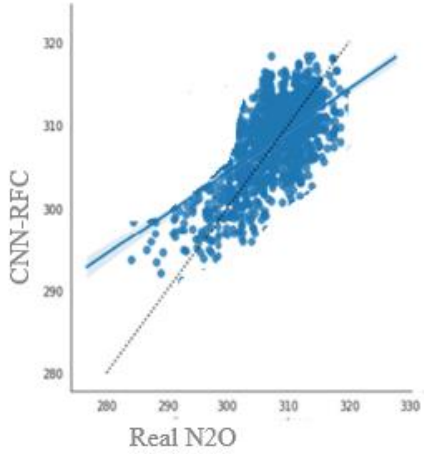
In the equation, o and p is the observed and predicted values, respectively, and m′ is the average of the observed values across all samples in the dataset. The performance of the proposed model is assessed using the previously specified metrics, and the results are shown in Table 1.

	RMSE	*MAE*	R^2	*SD*	*IOA*
CO_2	2.104	1.053	0.432	5.463	0.82
CH_4	13.231	10.032	0.473	10.587	0.85
N_2O	4.128	3.653	0.432	3.463	0.88
Temperature	4.825	4.043	0.603	5.334	0.82

Table.1: Performance metrics of CNN-RFC







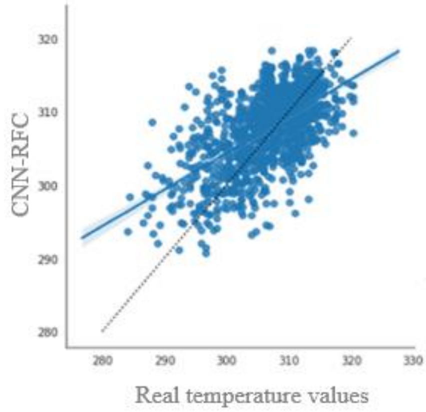


Figure.4: The CNN-RFC with the real data of GHG and temperature

The CNN-RFC, a proposed model vs. the true data as shown in fig.4, in which the black line denotes a perfect steady slope, and the blue lines indicates the regression line demonstrating the data as temperature, CO_2, CH_4 *and* N_2O. The forecasting results were studied in depth, and we came up with a reliable model for predicting climatic trends. As shown in fig.5, the CNN used to detect and predict climate change exposed that by 2030, there will be a considerable increase in temperature, possibly reaching high °C above the typical range of temperature. The algorithm also revealed the temperature increase is primarily due to the forecast the rate of atmospheric growth of CO2, which is likely to reach around 450 ppm, as well as the predicted concentration of CH4, which is expected to exceed 2000 ppb. These findings serve as an early caution system for countries around the world in terms of GHG emissions from industry. ML techniques have evolved into a dependable instrument for making the decisions and support future researches, despite the fact that they are still predictive models that employ existing data for learning.

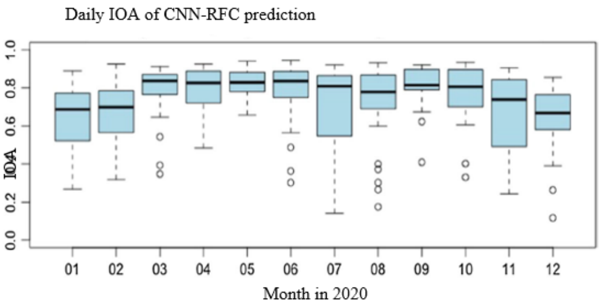


Figure.5: Daily IOA values predicted by CNN-RFC

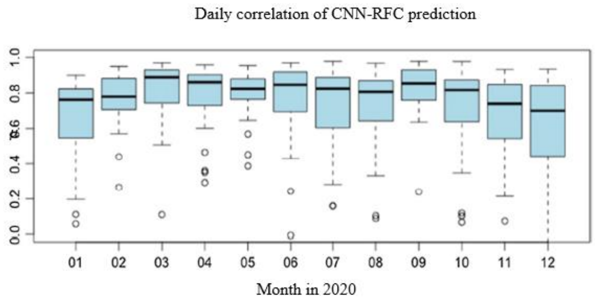


Figure.6: The correlation coefficient values are predicted by CNN-RFC

4.2 Comparative analysis

The comparative results of each network were evaluated to prove that the result of CNN-RFC is more efficient. The classification is based on the accuracy of the neural networks and the accuracy obtained fig 6 by the proposed model is better compared to other networks but LSTM provides slightly better accuracy than the proposed model Table 2.

GHG	*Method*	*RMSE*	*MAE*	*PEARSON*	*R2*	*SD*
CO_2	LSTM	6.132	5.127	0.329	0.561	3.674
	H-CNN	4.276	1.165	0.312	0.610	4.854
	CNN-RFC	2.104	1.053	0.325	0.432	5.463
CH_4	LSTM	17.135	11.624	0.237	0.467	14.142
	H-CNN	15.845	11.592	0.293	0.537	13.021
	CNN-RFC	13.231	10.032	0.138	0.473	10.587
N_2O	LSTM	5.322	4.127	0.391	0.561	4.674
	H-CNN	5.276	4.265	0.412	0.510	3.854
	CNN-RFC	4.128	3.653	0.357	0.432	3.463
Temperature	LSTM	5.312	4.184	0.325	0.575	3.654
	H-CNN	5.278	4.155	0.368	0.684	5.886
	CNN-RFC	4.825	4.043	0.293	0.603	5.334

Table.2: The comparison metrics between different methods that includes LSTM, H-CNN AND CNN-RFC

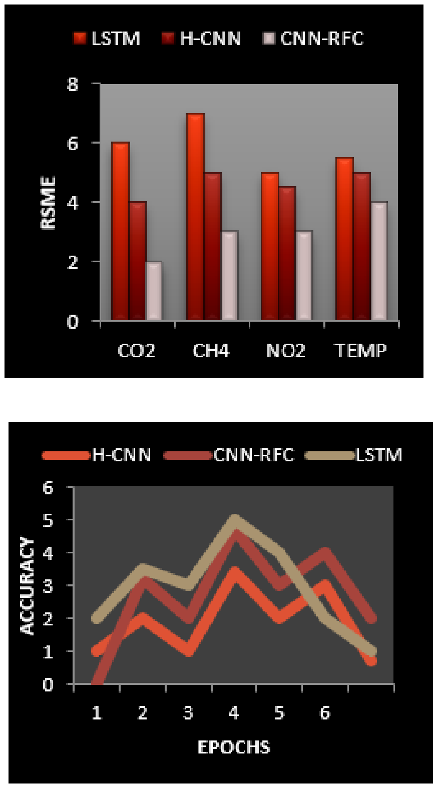


Figure.7: comparison between three models to determine accuracy

From the above comparison fig.7, it is obvious that the proposed model gains better accuracy range. The comparison findings of each model were used to demonstrate that the proposed system is more efficient. The classification is performed on the basis of the emission of GHG, temperature and the accuracy of the networks. The accuracy obtained by the CNN-RFC model is quite good with the low computational cost compared to other networks. On the other hand, LSTM determines better performance in obtaining the accuracy than the CNN-RFC. Based on this experiment, the suggested model has a poor classification rate of accuracy when compared to other networks. The accuracy range is slightly down compared to LSTM to overwhelm that issue; this model can improve in future and the future temperature changes is shown in fig.8

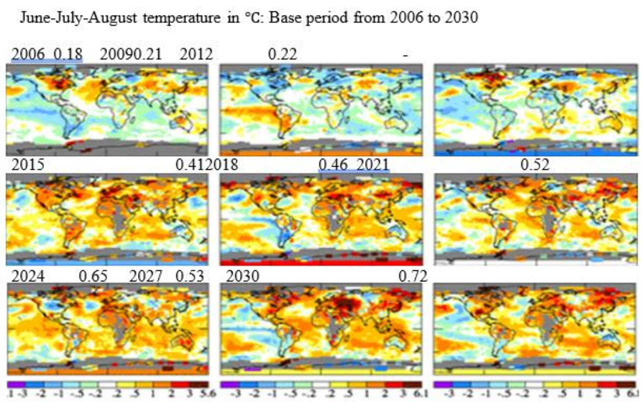


Figure.8: Climatic changes due to emission of GHG from 2006 to 2030

By this increasing emission of GG as shown in fig.9 have a wide range of environmental and health consequences will be araised in future. This rise will also affect the agriculture sector in all possible ways mainly leads to the lack of rainfall, drought and cause many diseases that affect plants and animals and so on. Air pollution and smogginess may cause respiratory issues, and they also contribute to climate change by trapping heat. Intense in climate change, lack in food resources, ecosystem breakdown, and increasing wildfires are all the impacts of climate change caused by the emission of GG. This increasing emission of GHG should be controlled and must reduce, otherwise it leads to very severe consequences in the society and thereby future cause many health issues in all living things. This emission is not only in agricultural sector, it is more in energy consumption and industrial sectors as shown in the fig.10 1shows the emission of GG in India and rapid increase in future.

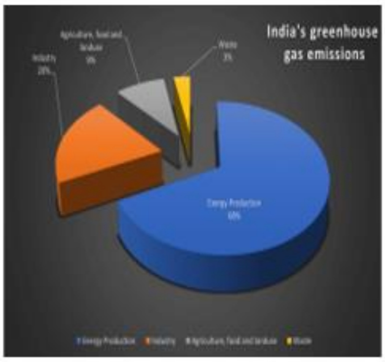


Figure.9: GHG emission in India

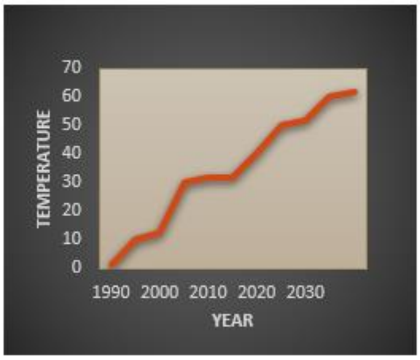


Figure.10: Increasing temperature in future

5. CONCLUSION

Global Warming is caused by the increase in GHG concentrations, which elevates the temperature on the earth atmosphere. Agricultural management practices that are modified may minimise GHG emissions. A DL model for predicting $CO_2, CH_4 and\ N_2O$ emissions from the agricultural sectors. This study concludes that the proposed model shows good prediction in response for $CO_2, CH_4 and\ N_2O$ emission along with the major effectual parameters for forecasting the climate changes in the earth's atmosphere. As a result, our research will assist farmers in gaining a better grasp of agricultural management strategies. Green biotechnology also provides a way to alleviate the omission of GG, which helps to alleviate the consequences in climatic changes. The only one reason for this climatic change is humans, so by future this emission should be controlled and reduced to develop a well and healthy environment.

CONFLICTS OF INTEREST

The author proclaims that there are no conflicting interests to disclose in this study.

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