ANALYSIS AND PREDICTION OF GREENHOUSE GAS EMISSION USING FEEDFORWARD NEURAL NETWORK

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Abstract

Greenhouse Gas (GHG) emission is caused by decomposition of biomass and dead plant residues, livestock enteric fermentation in ruminants, and burning of crop residues. As the concentration of GHG rises it raises the temperature on the globe causing the Global Warming. Alterations in agriculture management practices may reduce the GHG emission. Therefore, there is a need to analyze and forecast the GHG emission from Agriculture. We have built the Feedforward Neural Network using sequential neural network in keras for predicting CO_2 and CH_4 emission for Onion crop from open farm and poly house. We selected Onion for our study because Onion is one of the second most important commercial crops of the India. The GHG emission may vary in open farm and poly house for onion crop because the environment is controlled in poly house as compared to open farm. For this study we collected the field data of soil attributes, climatic attributes and CO_2, CH_4 greenhouse gases from the experiment field. We hyper tune the model with 3, 4 and 5 layers with different epoch. We have used Root mean squared error (RMSE), Mean squared error (MSE) and R-square as a coefficient of correlation for model prediction accuracy. Model predicted that Nitrogen, Moisture, Pressure, Humidity and Temperature are major affecting factors for emission of GHG for onion crop from open farm and poly house. The model indicates good prediction response for GHG emission with major influencing attribute for onion crop.

Keywords: Agriculture, Deep Learning, Feedforward Neural Network, Greenhouse Gas Emission, Soil.

1. Introduction

"Absorbing heat energy emitted from earth's surface and reradiating it back to earth's surface, thus contributing to the greenhouse effect which leads to Global Warming" is the property of greenhouse gas. According to World Meteorological Organization (WMO) Greenhouse Gas Bulletin the "global average concentrations of carbon dioxide (CO_2) reached 407.8 parts per million (ppm) in 2018 up from 405.5 parts per million in 2017". Fig. 1 shows how CO_2 concentration is increasing from1990 to 2018. According to Safwan Mohammed et al. [18] Agriculture is responsible for 13.5% emission of GHG and thus to variation in climate. Climate variation have an impact on agriculture in various way like rainfall pattern change, more floods, change in average temperature and sea level rise. Climate variation is directly affecting the food production across the globe. As per the United Nations Department of Economic and Social Affairs (UN/DESA) the global population increases to 9.7 billion people by 2050. The growth of population and demand for food require producing an adequate amount of food. So, different practices such as use of fertilizer, crop residue, soil management, land management etc. used by the farmers. These practices have their adverse effect on the environment to meet the needs like food demand, crop yield etc. these process frequently enhance the emission of GHG. One of the solutions to climate variation is to reduce the emission of greenhouse gases. Therefore, there is a need of

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analysis and prediction of greenhouse gas emission from agriculture sector.

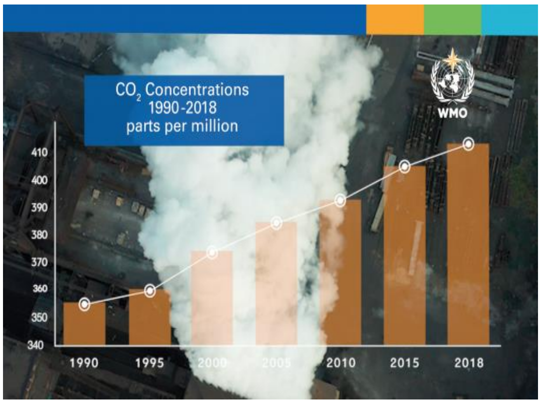

Figure 1.CO_2 concentrations from 1990-2019 parts per million [Source: 21]

The motive of the study is to design the Feedforward Neural Network (Deep Learning Model) for analysis and prediction of GHG i.e. CO_2 and CH_4 emission for Onion crop from Open farm and Poly house. We collected the field data of soil, climatic attribute and CO_2, CH_4 gases values from the farm. We also predicted the major influencing attributes for CO_2 and CH_4 emission for Onion crop from Open farm and Poly house. We selected Onion for our study because Onion is one of the second most important commercial crops of the India which is next to Potato. Also Onion can be grown up in a climatic situation such as temperate, tropical and subtropical climate. The GHG emission may vary in open farm and poly house for onion crop because the environment is controlled in poly house as compared to open farm. The paper is structured as follows: the Section I introduces the idea about emission of greenhouse gas from agriculture. Section II present survey of various work done, section III describe the methodology for analysis and prediction of greenhouse gas emission from agriculture. Section IV presents analysis of results obtained and section V provides the conclusion.

2. Literature Survey

Different studies are conducted to analyze and forecast the GHG emission from agriculture soil and climatic attribute for different crops. The survey shows some of the work done in this area. According to Kingsley Appiah et al. implemented fully connected two-layer feed-forward neural. They have used Levenberg-Marquardt algorithm for forecasting the emission of selected emerging economies using data from 1971 to 2013 from World Development Indicators and FAOSTAT database. Their result showed that the model errors are less than 0.05 and their model forecast potential carbon dioxide emission in emerging economic with greatest accuracy [15]. Forkuor G et al. implemented four statistical predicting models, for mapping soil samples to spatial distribution of six soil properties. Their result shows that algorithm work better than multiple linear regression for forecasting of soil properties [10]. Leopord Uwamahoro & Dr. Papias Niyigena used Long Short Term Memory recurrent neural network model for forecasting the greenhouse emission from agriculture activities in Rwanda. Their result showed high accuracy in prediction of 97.64% and 2.36% in the loss [16]. Alicja Kolasa-Więcek used ANN for forecasting direct N_2O emissions from Agricultural Soils. Their sensitivity analysis with multilayer perceptrons (MLP) 9-4-1 confirms that use of nitrogen fertilizer has the major role for N_2O emission. Also for formation of N_2O emission participate cattle and pigs are mainly important with MLP16-5-1 [1]. Chusnul Arif et al. have used ANN model for estimating GHG emission from paddy irrigation with different water management. Their result shows that the coefficients of determination (R2) values were 0.84 and 0.76 for CH_4 and N_2O prediction respectively with high precision [8]. Ashkan Nabavi-Pelesaraei et al. have used ANN for forecasting energy use and GHG emission of watermelon production system for three different farm sizes. Their result shows that ANN model with 11–10–2 structure works better with coefficient of determination (R2) as 0.969 and 0.995 for yield and GHG emission respectively [2]. B. Khoshnevisan et al. have used ANN for predicting GHG emission of Strawberry production. Their result shows that chemical fertilizer was the major significant feature for GHG emission. The ANN model with 11-6-10-2 structure works best with lower RMSE and MAE values for forecasting the output energy and GHG emission [6]. Homa Hosseinzadeh-Bandbafha et al. concluded that adaptive neuro-fuzzy inference system predicts energy output and greenhouse gas emissions more accurately than the ANN [12]. Similarly Guifang Liu et al. investigated total greenhouse gas emission for wheat production.

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Their result showed that N_2O, N fertilizer, compound fertilizer, electricity, and diesel oil were the main GHG emission sources [11]. Cai-Ma designed "a carbon emission prediction model of agroforestry ecosystem based on support vector regression. Seven carbon sources, including root decomposition, chemical fertilizer, pesticide, agricultural film, agricultural irrigation, agricultural machinery and farmland tillage, were selected as influencing factors of carbon emissions in agroforestry ecosystem. The experimental result shows that the model can predict carbon emissions of agroforestry ecosystem quickly and completely" [7]. Hyeon Ji Song et al. have suggested that Autumn straw application significantly decreased CH_4 intensity by average 24–65% over the spring straw application [13]. Safieh Javadinejad et al. have analyzed the monthly and seasonal methane gas. They conclude that rise in CH_4 concentration is majorly related to low vegetation cover and high temperature [19]. Johnson Masaka et al. have suggested that "improved agronomic practices for increased crop productivity can be used as a mitigation factor for reducing the contribution of agriculture in the global emissions of N_2O" [14]. Aung Zaw Oo et al. have assessed CH_4 emission in lowland rice farms. Their result shows CH_4 emissions at non-fertilized parts were more than those at fertilized part [4]. Andreas Kamilaris et al. did analysis how deep learning techniques applied to agriculture sector. Their analysis shows that deep learning provide good prediction accuracy as compared to existing image processing methods used in agriculture sector [3]. Dinesh Panday et al. have shown that there is relationship between greenhouse gases and soil pore space indices and soil water for corn/soybean [9]. B. J. Zebarth, et al. have analyzed and recommended that improved managing of fertilizer N can reduce nitrate intensity in corn farm [5]. Witsanu Attavanich analyzed and concluded that temperature and precipitation considerably establish the farmland values and greenhouse warming [20]. Mphethe Tongwanea et al. have compared different crop production and management practices for GHG emission. They suggested that, "mitigation plans of emissions from field crops in South Africa need to focus more on sustainable improvement of soil fertility, optimum application of synthetic N fertilizer and crop residues" [17]. Kerstin Jantke et al. did the survey of German farmers regarding reducing the greenhouse gas emission and complying with the governance program. They analyze that German farmers are familiar of variation in climate change and feel a responsibility of reducing greenhouse gas emissions [23]. H. Flessa et al. have analyzed aggregate greenhouse gas emission from two different farming patterns. Their result shows that moving to organic farming from conventional farming led to reduction in emission per hectare, but yield-related emission were not reduced [24]. Sylvia H. Vettera et al. have studied the association of Greenhouse gas emission with major food commodities production in India using Cool Farm Tool [25]. According to Grant, B et al. have used The Denitrification-Decompostion (DNDC) model to figure out the influence of change in management practices on N_2O emission. Their result shows that moving from cultivated land to grassland, conventional tillage to no-tillage and the reduction of summer allow in crop rotations increases C sequestration and decrease net GHG emissions [26]. Abderrachid Hamrani et al. have used machine learning algorithm namely classical regression, shallow learning and deep Learning LSTM for forecasting soil greenhouse gas emission. Their result shows that LSTM model give the good performance in prediction of N_2O and CO_2 fluxes [27]. After studying the research papers we found that most of the researchers either use soil or climatic variable for emission of GHG for crops like corn, rice, strawberry etc. but they have not compare the emission of GHG for same crop under the poly house and open farm cultivation. This study will help the farmers for better understanding of agriculture management practices.

3. Methodology and Material

A variety of machine learning models have been used for analysis and prediction of GHG emission in agriculture. We have built the deep learning model for analysis and prediction of GHG emission for onion crop from open farm and poly house. For this study is collected field data of soil and climatic attributes from Directorate of Onion & Garlic Research, Rajgurunagar, Pune (Maharashtra). We collected soil and climatic data from the farm during January 2020 to March 2020 weekly twice for experimental purpose. The soil attributes considered are N-P-K values (Nitrogen, Phosphorous and Potassium), pH values, Soil Type,

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Soil Temperature and Moisture. The Climatic attributes considered are Pressure, Temperature, Humidity, and Wind Speed. The GHG emission data considered are CO_2 and CH_4. The focus of this study is to analyze and predict the CO_2 and CH_4 emission for Onion crop from Open farm and Poly house. The study also finds the major influencing attribute for Onion crop from Open farm and Poly house. Fig. 2 shows the working of model.

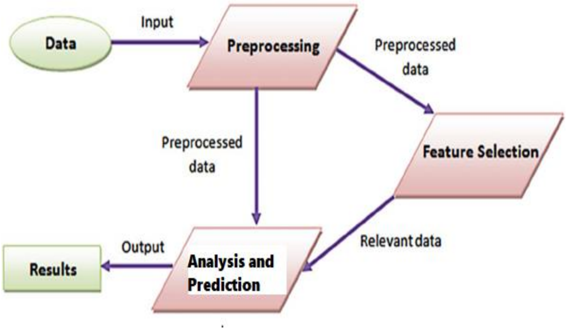

Figure 2. System Architecture

With the use of different sensors the attributes related to soil, climatic and GHG emissions are collected with Arduino UNO Microcontroller. The DHT11 sensor is a commonly used temperature and humidity sensor. Agrinex Solution SOIL DOCTOR PLUS (HC 106 NPKpH) is integrated kit is used to access primary nutrients (N-P-K) as well as pH levels of soil. For measuring the soil pH and moisture we used 2 in 1 Soil PH and moisture sensor. MQ-4 is a methane gas sensor that detects the concentration of methane gas in the air. The MQ-135 Gas sensors are used for measuring of CO_2 gas. Whereas the Google weather app is used for collection of climatic attributes. The data measured is directly saved on the cloud (Thingspeak) from where it can be downloaded. The preprocessing of the data is done like converting the text data into numerical. The text values of field Nitrogen, Phosphorus, and Potassium (NPK) is converted into 0, 1, 2 from high, low and medium. Further preprocessing is done using normalization. This dataset is normalized using minmax scalar function i.e. with normalization we change the soil, climatic and GHG emission data to common range. We further perform the feature selection to reduce the training time, over fitting and to improve the accuracy of the model. In the feature selection we select the features which are important to predict the response variable.

4.1. Feedforward Neural Network

Power of the model prediction is depends on the right adjusted weight and bias. The training phase performs feedforward i.e. calculate the predicted output and backpropagation which update the weights and bias. Each iteration of training phase performs these task i.e. feedforward and backpropagation. Neural Network mathematically it is written as follows,

$$\hat{Y} = \sum_{i=1}^{n} Wixi + b \qquad (1)$$

Where,
$\hat{Y}$ is output variable,
W is weight applied to layer
x input variables
b is bias
n is the number of observation used in experiment

We have used keras framework to create a feedforward neural network stacking layer by layer using Sequential model. The model consists of 4 layers including the input and output layer. The input layer or the first layer has 50 neurons and we are considering 11 input parameters with activation function ReLu. The second layer or the first hidden layer has 25 neurons with activation function ReLu. The third layer has 12 neurons using ReLu as the activation function. A dropout layer is added to optimize the model. The output layer uses sigmoid as the activation function to generate the final output. Through evaluation of analysis of results, the model was hyper tuned by optimizing the number of neurons, batch size and number of epochs. Using R-squared error function, Epoch=1000 was found to be optimal and was selected for the particular model minimizing RMSE and using MSE and R-Squared as metrics.

4. Result and Discussion

We tried to predict and analyze GHG emission values from soil and climatic attributes for Onion crop from Open field and Poly house. We used RMSE, MSE and R-Squared values for model performance.

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4.1. Prediction of CO_2 emission from Open farm

We use inbuilt function to find the weight for the important feature for prediction of CO_2 emission from open farm. For open farm environment humidity with weight 0.0020 ± 0.0002 followed by wind speed with weight 0.0005 ± 0.0001 are most important features for emission of CO_2. Fig. 3 shows the weight values along with features.

Weight	Feature
0.0038 ± 0.0001	Site
0.0020 ± 0.0002	Humidity
0.0005 ± 0.0001	Wind speed
0.0001 ± 0.0000	Pressure
0.0000 ± 0.0000	Moisture
0.0000 ± 0.0000	Temperature
0.0000 ± 0.0000	pH
0.0000 ± 0.0000	N
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation

Figure 3. Weight feature of soil and climatic attribute

We hyper tune the model with different layer i.e. 3 layer, 4 layer and 5 layer with different epoch values to get the best value for RMSE. The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0112 as compared to 3 layer and 5 layer model with 1000 epoch. Table 1 show the RMSE values with number of layer and epoch values and fig. 4 graph shows comparison of the number of epoch and error values. Lower the error good is the prediction model.

Table 1. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.0344	0.0313	0.0376
100	0.0280	0.0277	0.0466
150	0.0315	0.0274	0.0576
500	0.0173	0.0172	0.0135
700	0.0144	0.0133	0.0141
1000	0.0125	0.0112	0.0129

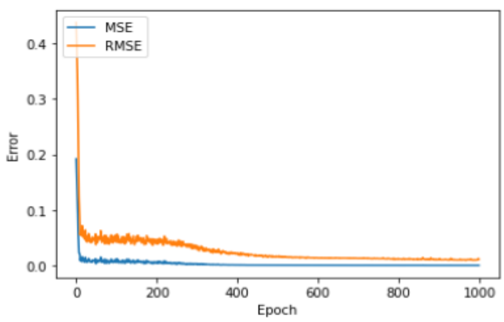
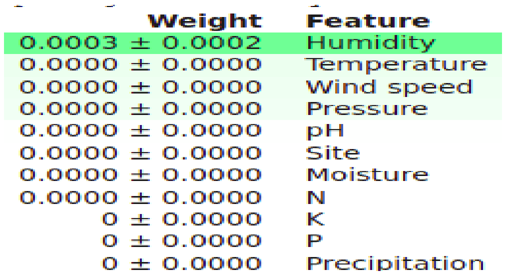


Figure 4. Feedforward Neural Network-Comparing errors with no of epoch

4.2 Prediction of CO_2 emission from Poly house

For poly house environment humidity with weight 0.0003 ± 0.0002 is most important feature as compared to other features for emission of CO_2. Fig. 5 shows the weight values along with features.



Weight	Feature
0.0003 ± 0.0002	Humidity
0.0000 ± 0.0000	Temperature
0.0000 ± 0.0000	Wind speed
0.0000 ± 0.0000	Pressure
0.0000 ± 0.0000	pH
0.0000 ± 0.0000	Site
0.0000 ± 0.0000	Moisture
0.0000 ± 0.0000	N
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation

Figure 5. Weight feature of soil and climatic attribute

The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0238 with 1000 epoch. Table 2 shows the RMSE values with number of layer and epoch values and fig. 6 graph shows comparison of the number of epoch and error values.

Table 2. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.0367	0.0504	0.0482
100	0.0281	0.0570	0.0515
150	0.0244	0.0462	0.0481
500	0.0255	0.0298	0.0398
700	0.0206	0.0292	0.0411
1000	0.0246	0.0238	0.0243

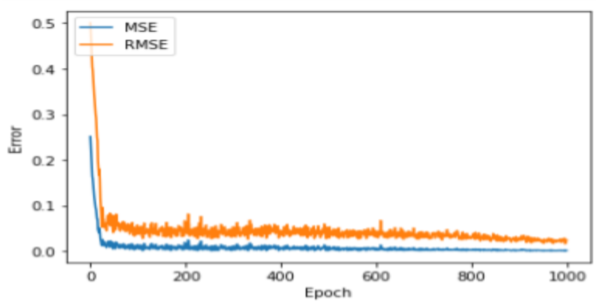


Figure 6. Feedforward Neural Network-Comparing errors with no of epoch

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4.3 Prediction of CH_4 emission from Open farm

For open farm environment pressure with weight values 0.0159 ± 0.0010, humidity with weight values 0.0144 ± 0.0008, temperature with weight values 0.0048 ± 0.0007 and wind speed weight values 0.0004 ± 0.0002 are most important features for prediction of CH_4 emission. Fig. 7 shows the weight values along with features.

Weight	Feature
0.0159 ± 0.0010	Pressure
0.0144 ± 0.0008	Humidity
0.0052 ± 0.0007	Site
0.0048 ± 0.0007	Temperature
0.0004 ± 0.0002	Wind speed
0.0001 ± 0.0000	Moisture
0.0000 ± 0.0000	pH
0.0000 ± 0.0000	N
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation

Figure 7. Weight feature of soil and climatic attribute

The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0171 with 1000 epoch. Table 3 shows the RMSE values with number of layer and epoch values and fig. 8 graph shows comparison of the number of epoch and error values.

Table 3. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.0555	0.0480	0.0524
100	0.0429	0.0471	0.0456
150	0.0425	0.0425	0.0370
500	0.0314	0.0254	0.0243
700	0.0249	0.0191	0.0203
1000	0.0222	0.0171	0.0183

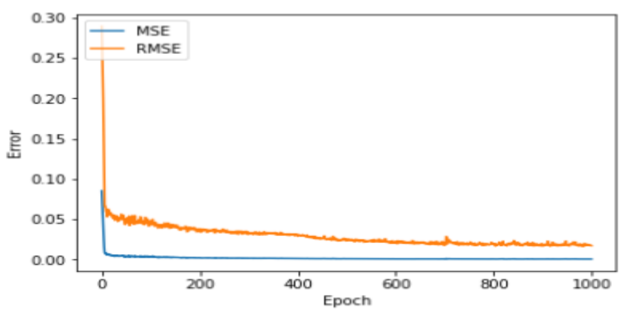

Figure 8. Feedforward Neural Network-Comparing errors with no of epoch

4.4. Prediction of CH_4 emission from Poly house

For poly house environment humidity with weight values 0.0141 ± 0.0020, pressure with weight values 0.0018 ± 0.0001, temperature with weight values 0.0008 ± 0.0002 and wind speed weight values 0.0006 ± 0.0003 are most important features for prediction of CH_4 emission. Fig.9 shows the weight values along with features.

Weight	Feature
0.0141 ± 0.0020	Humidity
0.0018 ± 0.0001	Pressure
0.0008 ± 0.0002	Temperature
0.0006 ± 0.0003	Wind speed
0.0000 ± 0.0000	pH
0.0000 ± 0.0000	Moisture
0.0000 ± 0.0000	Site
0.0000 ± 0.0000	N
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation

Figure 9. Weight feature of soil and climatic attribute

The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0312 with 1000 epoch. Table 4 shows the RMSE values with number of layer and epoch values and fig. 10 graph shows comparison of the number of epoch and error values.

Table 4. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.2706	0.0761	0.0599
100	0.2223	0.0643	0.0559
150	0.1768	0.0610	0.0566
500	0.0494	0.0413	0.0496
700	0.0448	0.0400	0.0438
1000	0.0424	0.0312	0.0342

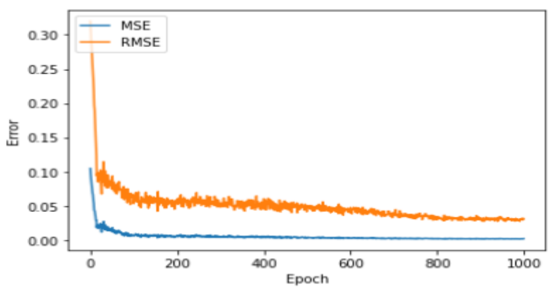

Figure 10. Feedforward Neural Network-Comparing errors with no of epoch

4.5 Prediction of total GHG emission from Open farm

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Pressure with weight values 0.040 ± 0.0001 is a major affecting factor for total greenhouse gases in open farm environment. Pressure plays major role while Humidity with weight values 0.0003 ± 0.0000 plays as minor role for total GHG emission from open farm. Fig. 11 shows the weight values with feature importance.

Weight	Feature
0.0040 ± 0.0001	Pressure
0.0003 ± 0.0000	Humidity
0.0000 ± 0.0000	Temperature
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation
-0.0000 ± 0.0000	Site
-0.0000 ± 0.0000	N
-0.0000 ± 0.0000	pH
-0.0000 ± 0.0000	Moisture
-0.0000 ± 0.0000	Wind speed

Figure 11. Weight feature of soil and climatic attribute

The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0054 with 1000 epoch. Table 5 shows the RMSE values with number of layer and epoch values and fig.12 graph shows comparison of the number of epoch and error values.

Table 5. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.0166	0.0120	0.0194
100	0.0114	0.0121	0.0154
150	0.0113	0.0109	0.0134
500	0.0101	0.0103	0.0125
700	0.0083	0.0078	0.0109
1000	0.0020	0.0054	0.0031

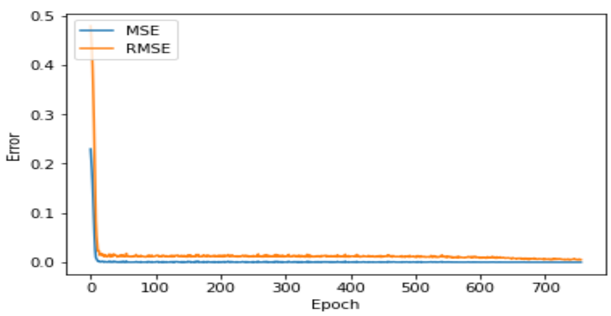

Figure 12. Feedforward Neural Network-Comparing errors with no of epoch

4.6 Prediction of total GHG emission from Poly house

Pressure with weight value 0.0009 ± 0.0001 is a major factor for emission of greenhouse gases for poly house environment while humidity with weight values 0.0001 ± 0.0000 as a minor factor. In general, throughout the analysis, Pressure and Humidity can be seen as constant factors for emission of GHG while other factors cannot be neglected but are important in specific manner. Fig.13 shows the weight values with features importance.

Weight	Feature
0.0009 ± 0.0001	Pressure
0.0001 ± 0.0000	Humidity
0.0000 ± 0.0000	Temperature
0.0000 ± 0.0000	Moisture
0.0000 ± 0.0000	Wind speed
0.0000 ± 0.0000	pH
0.0000 ± 0.0000	Site
0.0000 ± 0.0000	N
0 ± 0.0000	K
0 ± 0.0000	P
0 ± 0.0000	Precipitation

Figure 13. Weight feature of soil and climatic attribute

The experimental result shows that model with 4 layer gives good accuracy in terms of RMSE values i.e. 0.0106 with 1000 epoch. Table 6 shows the RMSE values with number of layer and epoch values and fig. 14 graph shows comparison of the number of epoch and error values.

Table 6. Number of epoch and layer wise RMSE values

Epoch	3 Layer	4 Layer	5 Layer
50	0.2203	0.0116	0.0613
100	0.0500	0.0139	0.0334
150	0.0231	0.0136	0.0175
500	0.0338	0.0140	0.0132
700	0.0199	0.0137	0.0247
1000	0.0198	0.0106	0.0228

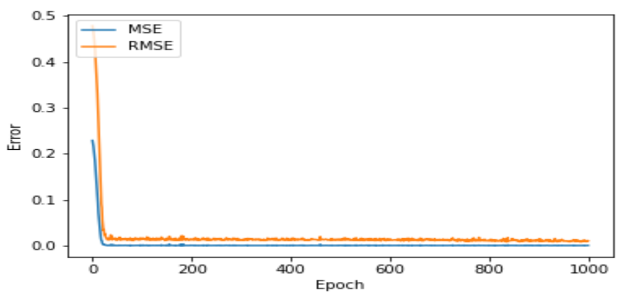

Figure 14. Feedforward Neural Network-Comparing errors with no of epoch

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5. Conclusion

As the concentration of GHG rises it raises the temperature on the globe causing the Global Warming. Modification in agriculture management practices may reduce the GHG emission. We have built the Deep Learning Model for predicting CO_2 and CH_4 emission for Onion crop from open farm and poly house. The GHG emission may vary in open farm and poly house for onion crop because the environment is controlled in poly house as compared to open farm. For this study we collected the field data of soil attributes, climatic attributes and CO_2, CH_4 greenhouse gases from the experiment field. We hyper tune the model with 3, 4 and 5 layers with different epoch. For Open farm and Ploy house the RMSE values for CO_2 are 0.0112 and 0.0238 and for CH_4 0.0171 and 0.0312 with 4 layer model with 1000 epoch. Deep Learning Model also predicted that Nitrogen, Moisture, Pressure, Humidity and Temperature are major affecting factors for greenhouse gases in open field and poly house environment for onion crop.

The study conclude that model indicate good prediction response for CO_2 and CH_4 emission along with major influencing attribute for Onion crop from Open farm and Poly house. Hence our study will help the farmers for better understanding of agriculture management practices.

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