APPLYING MACHINE INTELLIGENCE TECHNIQUE TO STUDY RADON EXHALATION FROM SOIL

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Abstract: A model has been prepared under KERAS, an artificial neural network software under PYTHON, to predict radon exhalation rate from soil due to its emission from radium, a radioactive material present in the soil which in turn originates from the decay of uranium, another radioactive material. The model has been built under machine intelligence technique using artificial neural network algorithm with the data set obtained from the radon study conducted in the Brahmaputra valley of Assam. The model not only predicts exhalation rate of radon of our own data set but also do the same for other region where similar study has been conducted by other workers.

Keywords: radium; radon; artificial neural network (ANN); radon exhalation

1. Introduction:

Radon is a colourless, tasteless and odourless radioactive gas originating from radioactive decay of Uranium, present in the earth cast. Its half-life (3.82 days) helps radon to travel significant distance in the medium where it is formed and there is a fair chance that radon concentration will enhance once it is inside a room. It appears as major health hazard if present in enhanced level inside a dwelling. So radon exhalation from the soil and its primary cause due to emission from radium should be studied with due consideration. Already a lot of works have been done in different parts of the world including India which can be found in the literature. A brief discussion on radon exhalation in some selected places in India and other parts of the world has been made in our earlier paper [1] . A positive correlation with fair degree of accuracy is observed in all the observations. The underlying mechanism of radon emission from radium present in the earth crust is primarily a nuclear phenomenon which is undoubtedly similar irrespective of the geographical and geological locations. It is acceptable that the amount of radium content in the soil depends on the geology of the particular area so the magnitude of radon emission will depend on the geology of the location. It is also true that final exhalation of radon from soil will primarily depend on the characteristics of the soil through which radon makes its passage.

2. Motivation:

A lot of works have done on radium content and corresponding radon exhalation from the soil almost all over the world. A positive correlation between radium content and radon exhalation from the soil has been reported with varying magnitude depending on the geographical location and geophysical condition of the concerned area. An attempt has been made in this paper to study the data obtained from different region in one platform to look for common characteristic in the overall radon exhalation process.

3. Methodology:

The artificial intelligence (AI) is defined as the mimicry of the cognitive behaviour of human brain by the machine. **Machine intelligence (MI)** is the branch of artificial intelligence where the computer system statistically learns from the data without being explicitly programmed. **Artificial Neural Network (ANN)** is a learning algorithm for a machine which functions similar to a human brain [2] [3].

In making this study, we have planned to implement **Artificial Neural Network (ANN)** to analyse the data obtained from different region. The advantage of this class of machine algorithm is that it can work well even in the absence of any model consideration, it does not require any parameters to be considered for its analysis and no mathematical formulation is required for the purpose. It is extremely data adaptive and self-learning tool. The underlying physical process which governs the passage of radon from its emission from radium to the final exhalation through the ground is controlled by various parameters, which include radium content in the soil, its nature, porosity, water content etc. The reason for adopting this particular technique is that even without considering all these factors, we can attempt to predict the radon exhalation from the soil.

We have analysed the data with the help of **Keras** which is basically a **Python** library used for studying **ANN** models. It wraps the efficient numerical computation libraries **Theano** and **Tensor Flow** and allows one to define and train neural network models in a few short lines of code [4].

A. The architecture of model implementation

The basic steps followed in implementing Keras for predicting radon exhalation from soil are given below.

1. Model definition: We implement Sequential model which is a linear stack of layers. We apply following code for its implementation.

```
from keras.models import Sequential

from keras.layers import Dense,
                         Activation

model = Sequential()

model.add(Dense(1, input_dim = 1,
          Activation = "linear"))
```

2. Compilation: Before training a model, we have configured the learning process, which is done via the compile method. It receives three arguments:
   - An optimizer – In our analysis, we have chosen stochastic gradient descent method as an optimizer for parameter selection of the model.
   - A loss function – It determines the mean of the square of the error, an error which determines the difference of the target variable and model evaluated value.
   - A list of metrics – In our analysis, it is the mean square error that is recorded as metrics.

```
from keras import optimizers

sgd = optimizers.SGD(lr=0.001)

model.compile(optimizer = 'sgd',
    loss = 'mean_squared_error',
    metrics= ['mse'])
```

3. Training: Keras models are trained on Numpy arrays of input data and labels. For training a model, the code is

```
model.fit(x_train,y_train,
validation_data=(x_test,y_test),
batch_size = 1, epochs = 100,
shuffle = True)
```

4. Performance evaluation of the model: This determines the closeness of the model in predicting the target value. It is done by the following code

```
model.evaluate(x_train,y_train,
               batch_size = 1)
```

5. Prediction on new data:

```
model.predict(x_test, batch_size=1)
```

6. Saving Model: Finally, the model is saved with the following code.

```
model.save()
```

B. Source of Raw Data

The data of radium content and radon exhalation rate from the surface of the earth, collected from different locations in the Brahmaputra valley of Assam, India which includes both industrial and urban locality [5] has been used in building a model based on **Artificial Neural Network (ANN)** using **Keras**. The basic data consists of radium content expressed in Bq-Kg^{-1} in the soil samples of the studied area and radon exhalation rate per unit area expressed in mBq-Kg^{-1}h^{-1} from the soil of those areas [5]. This has been done by collecting soil samples from the studied areas. The detail description of obtaining the two parameters can be found in the reference [6].

C. Data Pre-processing

The raw data from the studied area are first of all pre-processed before feeding to the algorithm. This is done by ***Scikit-Learn*** library [7] using the following code

```
from sklearn.preprocessing import
                        StandardScaler

scaler = StandardScaler()

scaled_data = scaler.fit_transform()
```

For training the neural network and model building, the whole dataset is split into training and testing part. A part (10%) of the whole data has been kept aside for testing the model accuracy in predicting the output. The schematic diagram of the workflow of splitting the dataset, model building, its validation, testing the level of accuracy and prediction is shown in Figure.

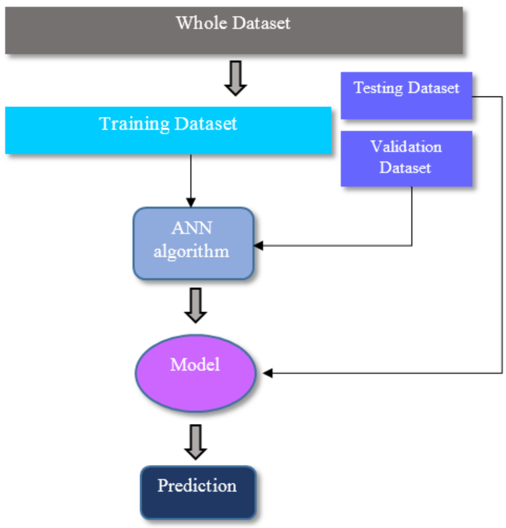

Figure 1: Workflow of data splitting into training and testing, model building and prediction.

Training data set fits the parameters of the model under supervised learning using the method of stochastic gradient descent and validation data set makes an unbiased evaluation of the model and tunes the parameters to avoid over fitting. After final evaluation of the model by testing data set, it is ready for prediction of unknown variable. The splitting of whole set of data into training and testing is done by ***Scikit-Learn*** library [7] using the following code

```
from sklearn.model_selection import
                      train_test_split

x_train, x_test, y_train, y_test =
             train_test_split(x, y,
             test_size=0.1,
             random_state=42)
```

D. Model output

Since the volume of data in the present study is less, we use testing data set for the validation of the model. The training loss and validation loss is shown in theFigure. The validation loss is less than training loss meaning that the model has been trained well. The score of the model, determined as mean squared error is found to be 0.0342.The value of the model parameter and the bias are 0.989 and 0.008 respectively.

E. Model accuracy

To check the accuracy of the model, we have plotted observed data against model predicted data. Red line represents the ideal case when observed data exactly tallies with the model predicted data. The dots are observed to be very close to the ideal line which implies that our model predicted data are very close to the observed data. With the same model, we have tried to test the data of other workers. Ranjan Kr. Kakati and his group studied the radium content and radon exhalation rate from the soil samples collected from Karbi Anglong district of Assam, India [8]. P C Deka and his group conducted radon study in the Brapeta district of Assam, India [9]. A positive correlation between radium content and radon exhalation was observed in their study. Chauhan studied the radon exhalation from the rocks of Aravali range of hills in the state of Haryana, India [10]. Khan and his group conducted study in the Etah district in Uttar Pradesh in Northern India [11] particularly in urban area. Musa and his group conducted the study of radium concentration and radon exhalation from the soil of Kerbala Governorate area of Iraq [12]. A positive correlation between two parameters was observed in their data sample. Elzain and his group conducted radon study in the Singa and Rabak towns in Sudan [13]. We have tested the data of all these workers in our model. All these data were pre-processed in ***Scikit-Learn*** library before feeding to the model for prediction and comparison. The accuracy of the model predictability has been tested by plotting observed values of radon exhalation of the studied area with that predicted by the model. This is shown in **Error! Reference source not found.**. It is seen that dots are either on the ideal line or very close to it implying that predicting power of the model is good. This proves that the model developed by our data set is applicable for other region as well.

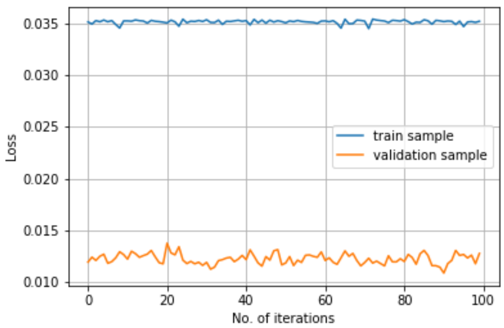

Figure 2: Training loss.

This encourages us to investigate the relationship between radon exhalations from the soil due to its emission from radioactive decay of radium in common platform considering data from different studied area. With radium content in the soil as input data, we have estimated the radon exhalation from the soil with the help of our own model. It is seen that data taken from different sources behave in a common manner. The normalised data of radon exhalation from the soil shows positive correlation with the radium content in the soil irrespective of the places on earth. To prove universal applicability of our model, we need to verify it with more data sample from different parts of the world.

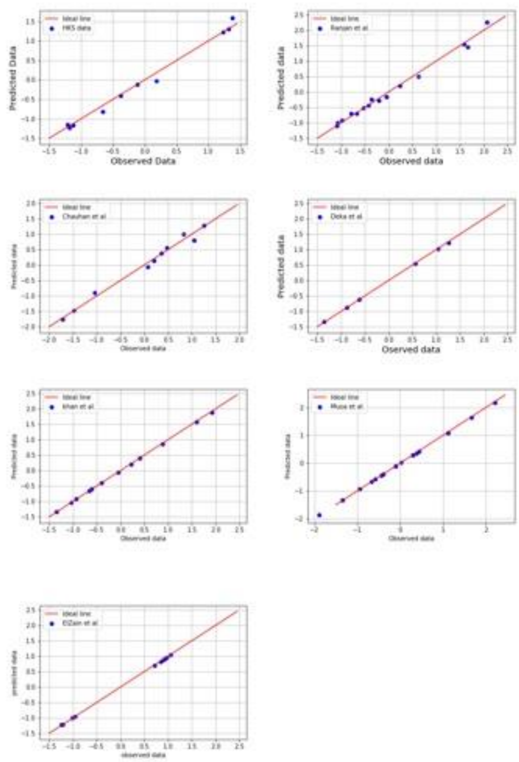

Figure 3: Comparison of model predicted value of radon exhalations with respect to the actually observed value.

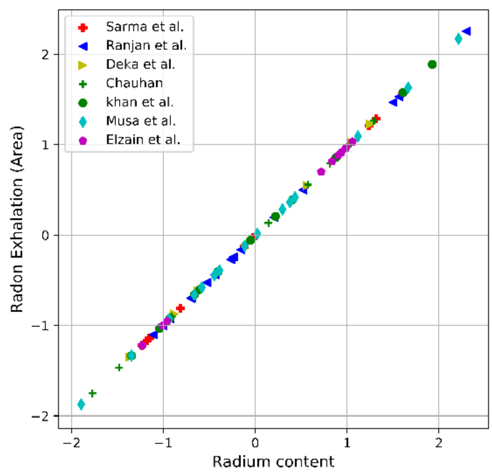

Figure 4: Prediction of radon exhalation from the surface of the earth with radium content as the input parameter.

4. Conclusion:

It is seen from the present study that **Machine Intelligence (MI)** technique through **Artificial Neural Network (ANN)** can be applied effectively in predicting radon exhalation rate from the soil. In the normalized scale data from different region follows the unique relationship between radium content and radon exhalation from the soil.

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