ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

CLIMATE CHANGE FORECASTING USING DEEP LEARNING

Hari Babu Guraka
Software Engineer, Cisco Systems Inc, San Jose, CA – 95134, United States

Article DOI: https://doi.org/10.36713/epra18552
DOI No: 10.36713/epra18552

ABSTRACT---

Climate change is defined as a long-lasting change in the mean weather patterns found on Earth. These changes are either natural, or human made. Since the 19th century, climate change has been on the rise. This is mostly due to igniting fossil fuels like gas, coal, and oil. These can lead to various problems like food and water scarcity, disease, increased flooding, extreme heat, and economic loss. It can also cause the sea levels to rise, and make oceans warmer and more acidic, and escalate human migration. It is referred to as the most significant threat to health on a global scale by the World Health Organization. Even if the efforts made to reduce future warming is successful, some effects will continue for tens of decades.

This paper attempts to forecast climate change based on the changes in temperature across the globe from the 19th century onwards. A deep learning-based time series model is built using Recurrent Neural Networks (RNNs) to forecast the average temperature. This model will attempt to predict future values based on historical data.

KEYWORDS—*Climate change, Deep learning, Recurrent Neural Network.*--

I. INTRODUCTION

Although climate change has been happening since the beginning of the ages, it has only recently become a problem worthy of concern. This is because there are a host of complications attached with these changes that make life difficult on Earth. Therefore, forecasting future changes and taking necessary precautions seems essential. This has so far been attempted using many methods. One of them is deep learning, which is the cutting-edge technology in today's times. Efforts have been taken to use deep learning to predict as well as forecast trends. They are also good at predicting climate change. But this algorithm is not without its defects. Forecasting time-series using feedforward neural networks is not easy, as it cannot handle sequential data, and considers only the current inputs without memorising previous inputs, which is necessary to maintain accuracy. This leads to inaccurate results with low accuracy. This opens room for newer models that can forecast time-series data by considering its limitation. This includes Recurrent Neural Networks (RNN). Based on David Rumelhart's work in 1986, this model is capable of handling all of these. An RNN can handle sequential data, by accepting the current input data, along with previously received inputs. As RNNs have internal memory, they can memorise previous inputs. This leads us to have better forecasting accuracy. Recurrent neural networks have a connection between the outputs and inputs of all neurons. This paper is about its implementation. Recurrent neural networks find their application in a variety of things, such as machine translation, robot control, speech recognition, speech synthesis, brain-computer interfaces, and so on, along with time-series forecasting. It also has the advantage of having various optimization methods that can be changed to train a better model. Recurrent neural networks are theoretically Turing complete and can run unpredictable programs to process unpredictable sequences of inputs.

II. LITERATURE REVIEW

Climate change is one in all the best challenges facing humanity, and we, as machine learning experts, may wonder how we will help. It is described in the paper how machine learning is a robust tool in reducing greenhouse gas emissions and aiding society to adapt to a changing climate. From smart grids to disaster management, we identify high impact problems where existing gaps is filled by machine learning, unitedly with other fields. Our recommendations encompass exciting research questions additionally as promising business opportunities. We turn the machine learning community to hitch the world effort against temperature change [4].

Climate change is challenging the functioning of society and may require significant adaptation to address changing weather patterns in the future. Machine learning (ML) algorithms have evolved dramatically, causing breakthroughs in other research areas and have recently been proposed to support climate analysis. Although a significant number of isolated features of the Earth system have been analyzed using ML technology, no more general application has been created to better understand the overall climate system. For example, ML helps identify communication links when complex feedback complicates characterization through direct equation analysis or Earth System Model (ESM) measurement and diagnostic visualization.

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

Artificial intelligence (AI) can be built on the basis of discovered climate links to enhance warnings for upcoming weather events, including extreme events. ESM development is of paramount importance, but we suggest focusing on leveraging ML and AI in parallel to better understand and leverage existing data and simulations [5].

In recent years, deep learning techniques have surpassed traditional models in many machine learning tasks. Deep neural networks have been successfully applied to address the problem of time series prediction, which is a very important topic in data mining. It has proven to be an effective solution because it can automatically learn the time dependencies that exist in time series [1].

III. SYSTEM ANALYSIS

EXISTING SYSTEM

FEED-FORWARD NEURAL NETWORK

A feedforward neural network is a neural network in which there are no cycles in the connections between the nodes. The opposite of a feedforward neural network is a recurrent neural network in which a particular path circulates. Feedforward models are the simplest form of neural networks because information is processed in only one direction. Data can pass through multiple hidden nodes, but it always moves in one direction, not in the opposite direction. Feedforward neural networks are usually considered in their simplest form as single-layer perceptrons. In this model, some input is supplied to the layer and weighted. Then each value is added to get the sum of the weighted input values. If the sum of the values exceeds a certain threshold (usually set to zero), the generated value is often 1, but if the sum falls below the threshold, the output value is 1. Single-layer perceptrons are an important model of feedforward neural networks and are often used in classification tasks. In addition, single-layer perceptrons can include aspects of machine learning. Using a property called the delta rule, the neural network compares the output of the node to the desired value and allows the network to adjust the weights through training to produce more accurate output values. This training and learning process creates a kind of steepest descent. In a multi-layer perceptron, the process of updating weights is similar, but the process is more specifically defined as backpropagation. In such cases, each hidden layer in the network is tuned according to the output value produced by the last layer [6].

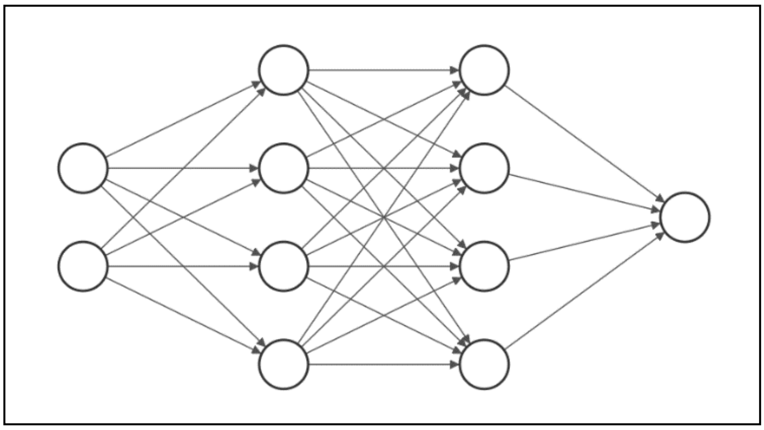

Fig. 1.Architecture of a Feed-Forward Neural Network.

LIMITATIONS OF EXISTING SYSTEM

1. A feed-forward neural network cannot handle sequential data.
2. It considers only the current input.
3. It cannot memorise previous inputs.
4. It has more parameters to optimise.

PROPOSED SYSTEM

RECURRENT NEURAL NETWORK

A recurrent neural network (RNN) is a type of neural network in which, over time, connections between nodes form directed or undirected graphs. This allows you to show dynamic behavior over time. Derived from feedforward neural networks, RNNs can use internal state (memory) to process sequences of variable length inputs. This allows it to be applied to tasks such as unsegmented networked handwriting recognition and voice recognition. Recurrent neural networks are Turing complete in theory and can run any program to process any input sequence. Traditional deep neural networks assume that the inputs and outputs are independent of each other, but the output of a recurrent neural network depends on the previous elements in the

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

sequence. The recurrent neural network standardizes various activation functions and weights and biases so that each hidden layer has the same parameters. Instead of creating multiple hidden layers, create one and repeat as many times as you need [7].

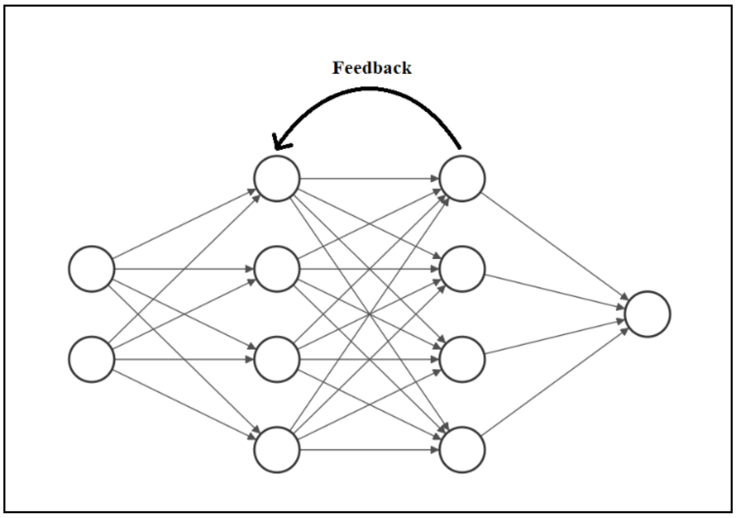

Fig. 2.Architecture of a Recurrent Neural Network.

Time Complexity—
The complexity of the calculation of a simple one-layer recurrent network is proportional to the length of the input sequence, O (n), both during training and during inference. Where n is the length of the input sequence. This is because we need to calculate everything before to get the last time step output.

ADVANTAGES OF PROPOSED SYSTEM

1. It can handle sequential data.
2. It can memorize previous inputs due to its internal memory.
3. Its weights can be shared across the time steps.

IV. RESEARCH METHODOLOGY

DESCRIPTION OF THE DATASET

SOURCE—
https://www.kaggle.com/berkeleyearth/climate-change-earth-surface-temperature-data/notebooks?datasetId=29

ATTRIBUTES—

```
['dt', 'AverageTemperature', 'AverageTemperatureUncertainty', 'Country']
```

DATA TYPES—

```
dt                                object
AverageTemperature               float64
AverageTemperatureUncertainty    float64
Country                           object
dtype: object
```

NUMBER OF RECORDS—

```
dt                               577462
AverageTemperature               544811
AverageTemperatureUncertainty    545550
Country                          577462
dtype: int64
```

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

GRAPHS—

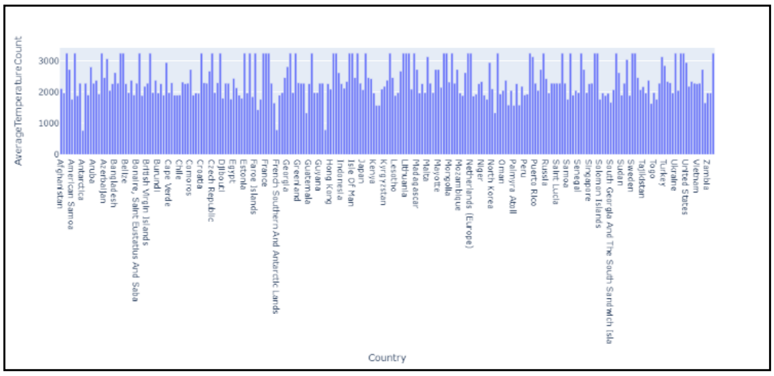

Fig. 3.Histogram showing the available records for each country.

Observations for a total of 242 countries are present in the dataset, and the above figure shows the number of records present by the name of the country. A vast majority have around 2000 records, while a few even have as high as 3000. We can also observe that a few countries fall short of the average by having records less than 1500. We will remove these observations during the data cleaning phase, to get more distributed results.

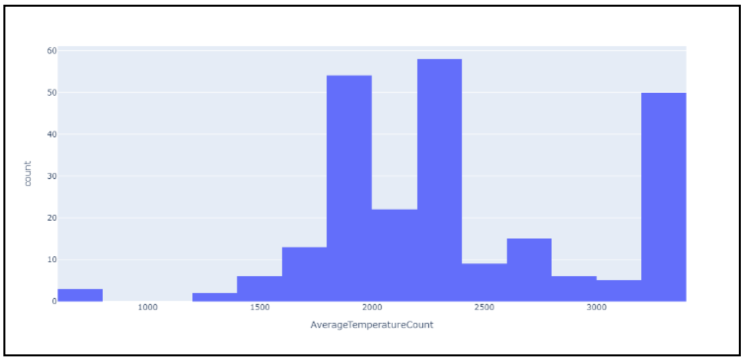

Fig. 4.Histogram showing the density of records based on number of countries.

This figure shows the number of countries that have a specific number of records. Around 3 countries have records less than 1000, and 6 have less than 1500. These are the records that we are going to remove. The countries on the other end go as high as having 3500 records each, which is about 50 out of the 242 total countries. On average, however, we see that most countries have a little over 2000 records for each of them.

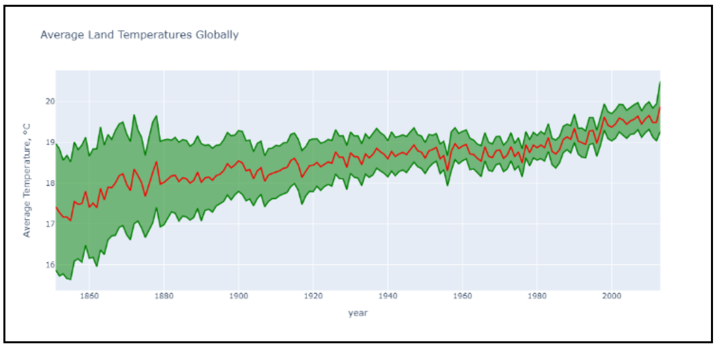

Fig. 5.Graph Showing the Average Temperature of Countries with uncertainty added.

The figure above shows a simple line plot of the data available for average temperature over the years. However, the lines on either side of it depict the average temperature uncertainty for each record. The actual temperature lies between both of these lines on the two sides, rather than the centre. For the purpose of this research, we will not be considering these lines, but only plot the average temperature, as our goal is to forecast time-series data using an algorithm that takes feedback. However, the diagram helps us in getting a better understanding of the dataset.

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

MODEL DESIGN

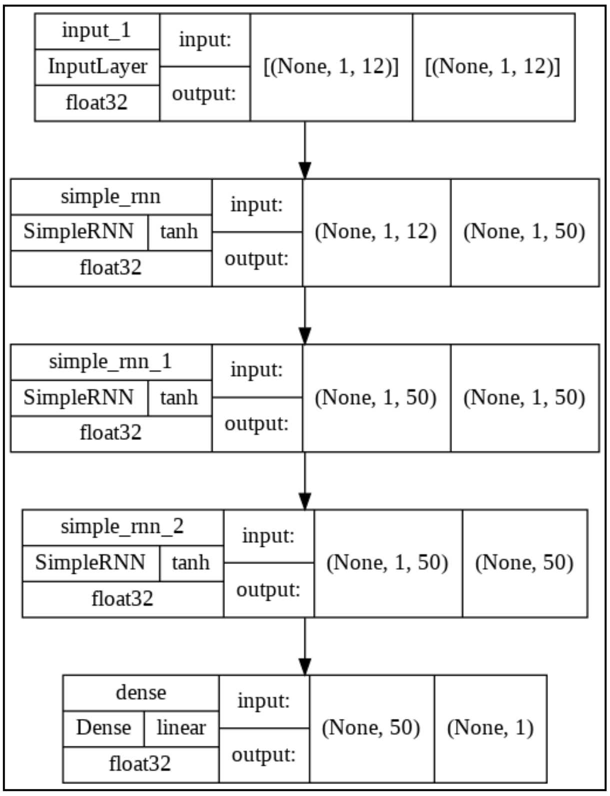

Fig. 6.Architecture of the model.

The model we have designed has a total of 5 layers; an input layer, three hidden layers, and an output layer. The hidden layers have 50 nodes each. The activation function that we will be using is 'tanh', with the 'adam' optimizer.

TESTING STRATEGY

MEAN SQUARED ERROR

Formula

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error
n = number of data points
Y_i = observed values
$\hat{Y}_i$ = predicted values

Fig. 7.Formula for calculating mean squared error (MSE).

In statistics, the mean square error (MSE) or root mean square deviation (MSD) of an estimator (a method of estimating an unobserved amount) measures the mean square of the error, which is the root-mean-squared difference between the estimated and actual values. MSE is a risk function that corresponds to the expected value of the square of the error loss. The fact that MSE is strictly positive (rather than zero) in most cases is due to randomness, or the fact that the estimator does not take into account information that may produce more accurate estimates. In machine learning, especially empirical risk minimization, MSE gives empirical risk (mean loss given an observed dataset) to true MSE (true risk: actual population distribution). It can be referred to as an estimate of (average loss if done) [8].

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

RESULTS

PREDICTION ACCURACY

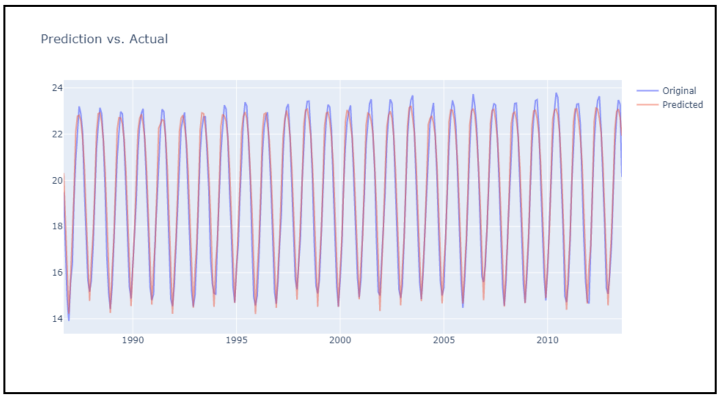

Fig. 8.Graph of predicted results with the original observations.

The blue line shows the recorded average temperatures over the years. The orange line shows the temperatures as predicted by the model. Plotting these two lines together, we can visually compare the accuracy of the predicted average temperatures with the original. As is obvious, the difference between the two is trivial. Testing the predictions with our testing strategy, a mean squared error of 0.05247303130424708 is obtained. This translates to an accuracy of 99.95%. The RNN's ability to "remember" the past input to predict the present output proves itself to be a wonderful advantage with time-series data.

ERROR

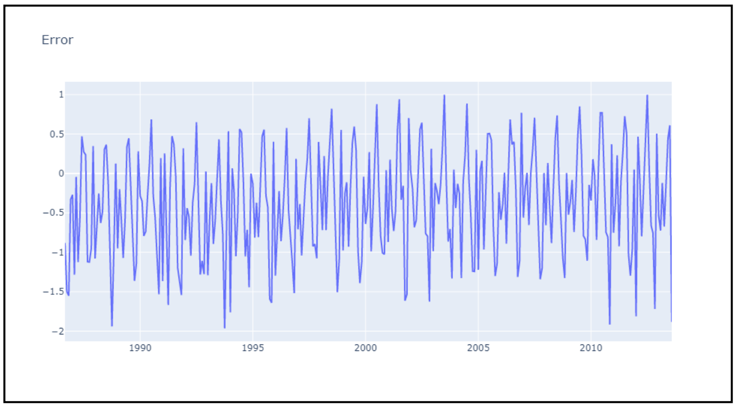

Fig. 9.Graph showing the errors obtained with the model.

The figure above reveals a closer look at errors of the model when compared with actual results. As observed before, it is negligible. On the positive side, the highest error is around 1 degree, while on the negative side it goes closer towards 2 degrees. The average of these differences on both sides could be added to the predicted future value, to get a result very close to optimal for a deep learning model.

CONCLUSION

We have observed the shortcomings of the traditional feed-forward neural networks and seen how Recurrent Neural Networks (RNNs) overcome them. While feed-forward neural networks pass the data forward from input to output, recurrent networks have a feedback loop where data can be fed back into the input before it is passed forward again for further processing and output. This is especially helpful in training time-series forecasting models, as this model is better equipped to handle sequential data, and also shares its weights across the time steps.

FUTURE ENHANCEMENTS

A good alternative to try is the Long Short-Term Memory Network (LSTM) model. This model was developed to overcome the vanishing gradient problem that can be come across when training traditional RNNs. LSTMs also have the advantage of relative insensitivity to gap length, over RNNs, hidden Markov models and other sequence learning methods in various applications. They are well-suited to train models that solve problems requiring long-term temporal dependencies [9]. Another improvement to try is to tune the hyperparameters to find the optimal accuracy of the model.

ISSN: 2347-7431
EPRA International Journal of Climate and Resource Economic Review
-Peer Reviewed Journal
Volume: 12 | Issue: 7 | October 2024 || SJIF Impact Factor (2024): 8.298 || Journal DOI: 10.36713/epra1213

REFERENCES

1. *An Experimental Review on Deep Learning Architectures for Time Series Forecasting | International Journal of Neural Systems. (n.d.). Retrieved May 24, 2022, from https://www.worldscientific.com/doi/abs/10.1142/S0129065721300011*
2. *"What Is Climate Change? | United Nations." United Nations, https://www.un.org/en/climatechange/what-is-climate-change. Accessed 22 Mar. 2022.*
3. *"Climate Change and Health." WHO | World Health Organization, https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health. Accessed 22 Mar. 2022.*
4. *"[1906.05433] Tackling Climate Change with Machine Learning." ArXiv.Org, https://arxiv.org/abs/1906.05433. Accessed 22 Mar. 2022.*
5. *Huntingford1, Chris. "Machine Learning and Artificial Intelligence to Aid Climate Change Research and Preparedness - IOPscience." ShieldSquare Captcha, 22AD, https://iopscience.iop.org/article/10.1088/1748-9326/ab4e55/meta.*
6. *Contributors to Wikimedia projects. "Feedforward Neural Network - Wikipedia." Wikipedia, the Free Encyclopedia, Wikimedia Foundation, Inc., 7 Apr. 2005, https://en.wikipedia.org/wiki/Feedforward_neural_network.*
7. *Contributors to Wikimedia projects. "Recurrent Neural Network - Wikipedia." Wikipedia, the Free Encyclopedia, Wikimedia Foundation, Inc., 7 Apr. 2005, https://en.wikipedia.org/wiki/Recurrent_neural_network.*
8. *Contributors to Wikimedia projects. "Mean Squared Error - Wikipedia." Wikipedia, the Free Encyclopedia, Wikimedia Foundation, Inc., 27 Mar. 2003, https://en.wikipedia.org/wiki/Mean_squared_error.*
9. *Contributors to Wikimedia projects. "Long Short-Term Memory - Wikipedia." Wikipedia, the Free Encyclopedia, Wikimedia Foundation, Inc., 16 Apr. 2007, https://en.wikipedia.org/wiki/Long_short-term_memory.*