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GLOBAL CLIMATE PREDICTION USING DEEP LEARNING

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ABSTRACT

Climate scientists are gaining an understanding and data of the past and are projecting what the future climate might be like through applying the climate models. A climate model is like a Virtual Earth, it's designed to mimic the real world, so that scientists can forecast future scenarios of climate changes. Climate models are composed of computerized representations of components that represent the atmosphere, ocean, sea, ice, surfaces and other processes. Climate models do not rely on speculation, they describe the climate system with mathematical equations based on the physics and solved with high advanced computers. This research presents a significantly Climate forecasting model using a deep convolutional Long Short-Term Memory (LSTM) to forecast temperatures world widely. New developments in this model include the next-days prediction with Convolutional LSTMs mapping of past climate change to project future climate change since the observed changes. In addition, the model of unsupervised Deep Learning networks is for tackling climate patterns detection problems and the improvements Recurrent Neural Network-RNN architecture by minimization the loss function over multiple sequence steps. Our model is considered one of the best models comparing with others, due to its high testing accuracy (100%).

Keywords—*Artificial Intelligence, Neural Network, Deep Learning, Global Climate Prediction*

1. INTRODUCTION

Humans learn from their past experiences and machines follow instructions given by humans, but what if humans can train the machines to learn from the past data and do what humans can do much faster well, that's called machine learning. See Figure 1, it's a lot more than just learning, it's also about understanding and reasoning. There are many machine learning algorithms quite easy right comes in it learns.

The data builds the prediction model and when the new data comes in, it can easily predict for better data [1]. These models will be accuracy and there are many types in the machine learning like supervised learning, unsupervised learning or reinforcement learning.

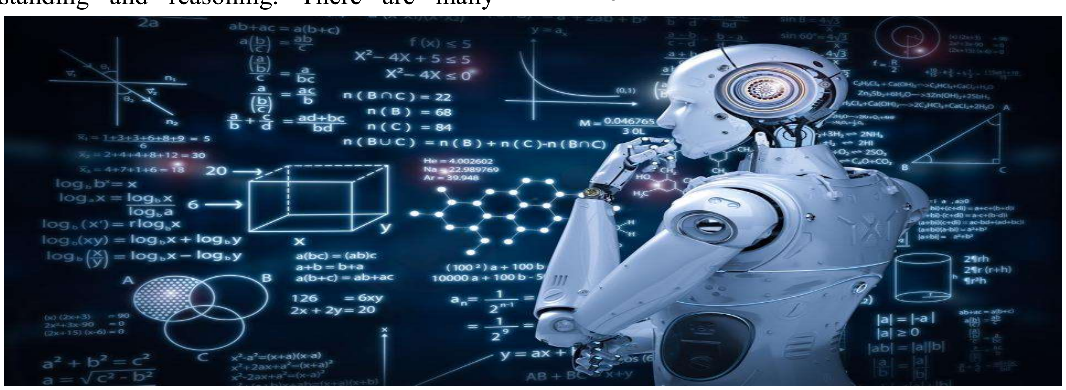

Figure 1: Machine Learning [2]

There's some amount of labeled truth data maybe the algorithm knows. If it won the game or lost the game but that information is partial. It doesn't know if this intermediate move was a good move or a bad move, so that's another example of semi-supervised learning and there's fundamentally this feedback in a lot of these systems there's feedback signal to modify your system or some [3].

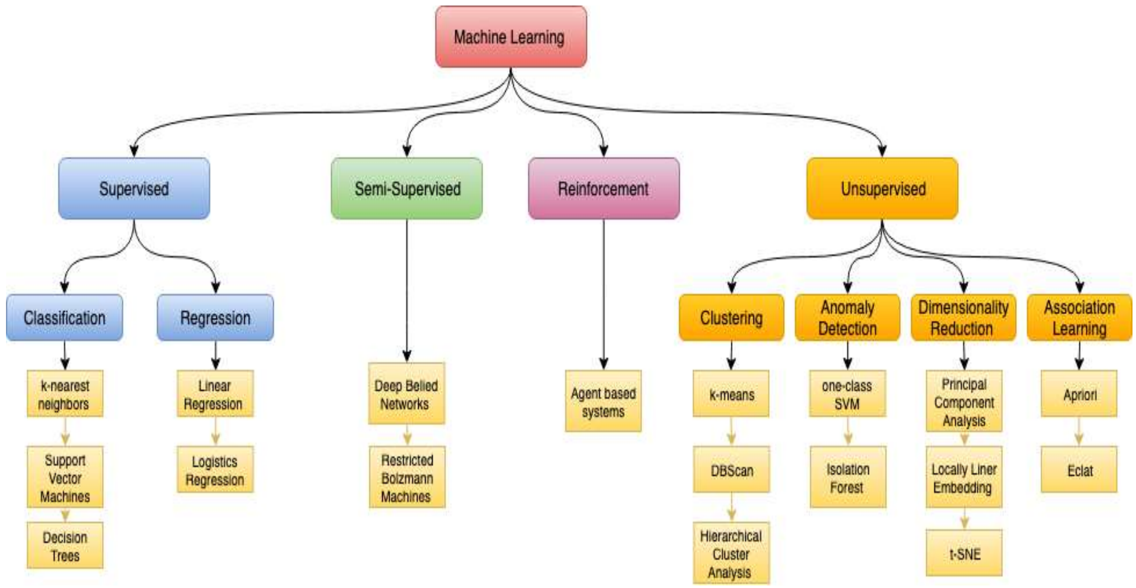

Figure 2: Machine Learning types

One of the most difficult duets in supervised machine learning is Prediction. Normally the target values are laborious to get, that is the reason why we want to automate this task. The prediction is a big exception, because data are virtually unlimited and no need to label the data. For that reason, Weather prediction belongs to the semi-supervised learning tasks. The learning is belonging to the group of supervised learning as our model has clear prediction values that are tested by a loss function. However, since the values are implicitly provided, the training data consistent with those of unsupervised learning tasks.

Training a computer to learn like a human brain, that's deep learning. Sometimes referred to as deep neural networking or deep neural learning, it's associated with artificial intelligence, and through deep learning computers, learn to recognize patterns and identify abstract objects.
To understand deep learning, imagine a toddler learning about dogs. Let's say the toddler learns about dogs by pointing to objects, with the parents replying, "Yes, that is a dog," or "No, that is not a dog." As the toddler continues to point to objects, he or she becomes more aware of dog features, like a tail and ears, and fur and four paws. The toddler is clarifying a complex abstraction.
The same concept of a dog, by building a hierarchy of which each level of abstraction can be created with knowledge that was gained by the preceding layer of the hierarchy. If you've ever seen a program that can recognize a flower species based on a photo, or song based on the sound of someone humming it, that is a result of a neural network. Beyond image and song recognitions, deep learning applications can be found in speech recognition and translation software, and even self-driving cars.
Deep learning has its limitations, however. Deep learning models learn through observation, and they only know what they're trained on. A deep learning model trained on a small or irrelevant dataset will learn in ways that aren't ultimately useful to the all tasks at hand. Figure 3 shows that the historical progress of AI to reach the Deep learning.

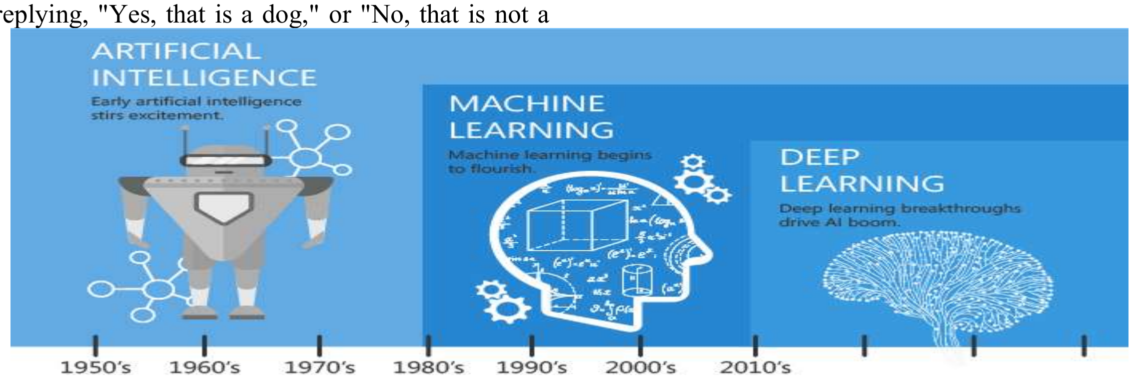

Figure 3: Deep Learning[3]

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2. GLOBAL CLIMATE

Climate change is a hot topic and most climate models agree that humanity's current actions will have relatively, little effect on the expected climate in the year 2050, so there is little variation in predicted outcomes. Let's fast forward to see what the world will look like in 2050. The world population is now 9.7 billion people, carbon dioxide levels are at around 500 parts per million, global temperatures have increased by 2 degrees since pre-industrial times [4]. This increase in temperature disproportionately affects the globe coastal areas are less affected than interior areas. Between June to August, it has the largest temperature increases. Sea levels have risen by 30 centimeters so far this century the southern Brazilian amazon lost 56 percent of its forests due to weak governance.

This widespread deforestation caused a decrease in rainfall in the region. Globally mean annual precipitation has decreased of the world's population now lives in urban areas. On average cities in the northern hemisphere today have climates like cities more than 620 miles south had three decades ago [5].

There is a shift of warmer temperatures north by about 12 miles per year cities are struggling to provide adequate water and cooling and increased air pollution has led to an increase in heat stress and respiratory disorders such as asthma air conditioning decreases heat stress, but makes air pollution worse cities have implemented some strategies.

That majorly decrease heat related mortality there are now enhanced tree canopies and more reflective surfaces, that absorb less heat as always. Those living in poverty and other vulnerable individuals such as the elderly are hit hardest by heat waves, but fortunately early warning and response systems make heat waves far less deadly. In Europe temperatures have increased yearly round with average increases of 3.5 degrees Celsius in summer and 4.7 degrees Celsius in winter compared to 2000.

London which used to be damp and cold earlier in the century is now as hot and dry as Barcelona was. There has also been an increase in infectious diseases such as vector-borne and water-borne diseases mental health disorders such as depression are rising due to more frequent natural disasters.

It's estimated that in 2010 there were 3.3 million premature deaths due to air pollution in 2050. There are 6.6 million deaths 358,000 of which are from ozone mortality due to air pollution was 50 percent higher in urban environments in 2010. Today it's 90 percent higher in urban environments the heat has increased the number of lost workdays in many parts of the world near the equator in southeast Asia, West and central Africa and central America, there has been an 18 increase in lost work days reduced work capacity has hit the economy hard especially outdoor workers.25 million more children are undernourished compared to 2020 and the prevalence of stunted growth is increasing.

Food prices are increasing rapidly especially for staples like corn and rice whose prices are double what they were three decades ago. Plant diseases have increased substantially while the nutrient value of some crops has diminished. Protein content in wheat and rice has decreased as has iron and zinc in rice soybeans wheat and peas we've tried to mediate this by increasing crop diversity planting drought and salt-resistant crops using drip irrigation and greenhouses. Food production processing transport and marketing are consistently disrupted by changes in rainfall and temperature increasingly frequent and damaging.

Weather anomalies as well as growing numbers of pests and diseases poor diet causes decreased earning potential and increased health care costs and families get trapped in a multi-generational cycle of poverty. The difference between the rich and poor grows ever larger extreme weather events result in forced migration and exacerbate tensions around scarce. Fresh water and fish stocks political instability grows hand in hand with food scarcity.

Cities in the tropics experienced less of a temperature increase than ones nearer the poles but there are now more frequent extreme precipitation events and droughts are more severe drought is one of the most widely damaging.

Climate conditions causing and exacerbating water and food security issues regions, like the middle east are hotter and drier than ever putting a great deal of stress on food production the increased frequency and intensity of droughts has also resulted in increased dust activity. North Africa is the main hub of dust generation followed by central Asia and China dust from Africa accelerates algal blooms in the southeast coast of the USA harming marine.

Life humans don't do well with the dust either inhaling, this dust has significant health impacts causing and exacerbating cardiopulmonary conditions. Chronic exposure is associated with silicosis asthma cognitive decline Alzheimer's disease and arsenic toxicity. It's associated with valley fever in the USA meningitis in North Africa and tuberculosis in India increased. Drought has also resulted in much more prevalent wildfires the particulates from these fires cause hundreds of thousands of premature deaths.

Each year on the one hand there are droughts on the other there are heavier precipitation events heavier precipitation events result in more waterborne diseases, for example heavy rain can result in sewage overflow which results in an increase in gastrointestinal illness flood water overflows with viruses [6].

In addition to an increase in waterborne diseases a warmer climate results in increased exposure to vector-borne diseases. This is because rising temperatures changed the rates of survival and reproduction of vectors and pathogens in the first 20 years of the 21st century.

By 2030 we need to stop the continuous increase in global temperature, but if we will not be able to stop, and if we fail to meet the deadline in eight years, at that certain point, it may become irreversible. The global mean temperature map will be increased, according to the National Aeronautics and Space Administration (NASA) data. Meanwhile the goal of the 2030 deadline set by the United Nations is to maintain the global temperature average lower than 1.5 degrees Celsius [18].

This can be done by eliminating carbon emissions, countries that produce the most carbon dioxide emissions such as China, United States, India, and Russia should be the first to decrease their emissions so that the plan will be more effective. We should encourage them to do those things because the effect will not be limited to their countries. Developing countries should assist by improving their ways of living so that they would contribute in the future. However, these are not the only things big countries can do.

3. PROBLEM STATEMENT

By 2030 we need to stop the continuous increase in global temperature, but if we will not be able to stop, and if we fail to meet the deadline in eight years, at that certain point, it may become irreversible. The global mean temperature map will be increased, according to the National Aeronautics and Space Administration (NASA) data. Meanwhile the goal of the 2030 deadline set by the United Nations is to maintain the global temperature average lower than 1.5 degrees Celsius [18].

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Although, dealing with large datasets is a major challenge in climate science research especially that most real-world time series datasets are multivariate and are rich in dynamical information of the underlying system, we may be able to solve the system of equations for these properties and every one of these grid points this involves millions and millions of calculations because of computing and other limitations. Some processes and climate models such as those representing clouds are described only approximately using representations called parameterizations.

These parameterizations are an important source of uncertainty in climate. Small numbers of climate researchers have developed and apply the complex comprehensive models. It is required to understand the past and future situation of the climate the predicate which will help the world's policymakers about the changes in climate.

Using the normal models, to experience a modeling of the temperature change, by looking at the average temperature for each month as simulated and are more difficult to be used at an international level because the effects of weather and variations of climate are more evident at those scales. Our climate model using Artificial Intelligence (AI) to has more reliable tools in assisting the scientists in understanding the past climate change and to predicate the future change for many years.

4. STUDY OBJECTIVES

- Develop an unsupervised (semi-supervised) model for Climate prediction model.
- Present a new Long Short-Term Memory LSTM-based learning approach to solve the random weight initialization problem of Deep Long Short-Term Memory (DLSTM).
- Propose a robust forecasting application based on the time series maps, which could be used to convert those observations into patterns that can be utilized easily for future projections.
- Help the scientists and policymakers, in their resolving to act and consider potential benefits of reducing climate change technologies.

5. RECURRENT NEURAL NETWORKS(RNN)

Neural Network is a type of machine learning model that mimics the human brain or have a brain like structure fundamentally. Neural Networks take in data and then train themselves to recognize the pattern in this data and then predict the outputs for each new set of similar data at its roots. A neural network is based on a network of mathematical equations moving on.

The mechanics of a basic neural network as Figure 4, the ideal neural network as you can see there's an input layer one or more hidden layers and an output layer. The input layer consists of one or more features or input variables or independent variables which are here denoted as X1, X2 moving on to X [28].

The hidden layer consists of one or more hidden nodes or hidden units and similarly the output layer consists of one or more output units. The given layer can have as many nodes as you want and similarly a given neural network can have as many layers as needed generally more nodes and more layers allow the neural network to make much more complex calculations.

Let's take up an example to understand your networks suppose we have a photograph of a dog and we want to build a neural network which tells us which breed the dog belongs to by feeding a neural network to create a set of images of different breeds of dog. It can return exact read from a subjective image as an output so how exactly does it do that. Neural Network is nothing more than a network of equations so each node in a neural network is composed of two functions a linear function and an activation function which ultimately determines which node in the following layer gets activated. Activation function as a characteristic match feature which results in a number between 1 or 0 what happens is that the input image is fed to a linear function of each node and results in a value z then this value Z is fed to activation function which determines if the characteristic feature is a match or not. Each node ultimately determines which node in the following layer gets activated until it reaches an output this is what you can call as a fundamental essence of a neural network [7] [8].

Let's discuss types of neural network we have in machine learning there are several types of neural networks but we have three main types that 1) Artificial Neural Networks: These are the ones which are composed of a collection of connected nodes that takes an input or a set of inputs and returns an output number, as shown in Figure 4 2) Convolutional Neural Networks or CNN's. A CNN is a type of neural network that uses mathematical operations like convolution instead of general matrix multiplication in at least one of their layers number. 3) Recurrent Neural Networks or are a Dense Recurrent Neural Networks are a type of a n ends where connections between nodes form a digraph along a temporal sequence allowing them to use their internal memory to process variable length sequences of input because of this characteristic. RNNs are exceptional at handling sequence data like execution or audio recognition lastly neural networks are also used in self-driving cars, character recognition, image compression, stock market prediction and has a lot of other interesting applications.

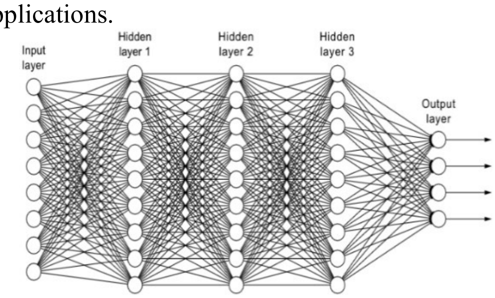

Figure.3: Architecture of Neural Networks [5]

RNNs are a class of artificial neural networks specialized in approaches that are effective at processing sequential information. The main strength of an RNN is the capacity to memorize the results of previous computations and use that information in the current computation.

This makes our NN models suitable to model context dependencies in inputs of arbitrary length so as to create a proper composition of the input which is the perfect fit for natural language processing applications, as we are feeding a sequence of words into the RNN, as presented in Figure 5.

The state gets updated for each word being input as a result the state essentially becomes a representation of all the words which have been processed so far and since the state gets updated in a sequential manner.

The state will also contain information about the order of the words as well as the words themselves [9]. Let's take an example sentence of deep learning is hard but fun and consider the states at each step as the RNN is processing this sentence when deep is fed into the RNN. The state contains the representation of just the word deep next when we feed learning into the RNN. It will update the state which had a representation of just deep to now contain a representation of deep + learning as the RNN continues to get the words from the sequence.

The final state contains the representation of deep learning is hard but fun the final state of the RNN contains both semantic information of the words in the sentence as well as sequential information regarding the order of the words which is perfect to understand the sentence since it works just like our brain. The uses of recurrent neural networks go far beyond text generation to machine translation image captioning and authorship identification although these applications will not displace any humans it's conceivable that with more training data in the larger model a neural network would be able to synthesize new reasonable patient abstracts.

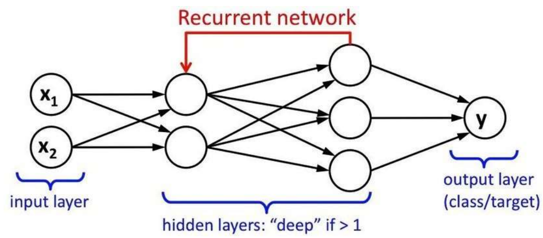

Figure 4: Recurrent Neural Networks [5]

5.1 Forward pass and Back propagation

Short-term memory and vanishing gradient are due to the nature of back propagation algorithm used to Train and optimize neural networks and to understand why this is let's take a look at the effects of back propagation on a deep feet board neural network training and neural network has three major steps first it does a forward pass and makes a prediction second it compares the prediction to the ground truth using a loss function [31]-[35].

The loss function outputs an error value which is an estimate of how badly the network is performing. It uses the error value to do back propagation which calculates the gradients for each node in the network. The gradient is a value used to adjust the network's internal weights allowing the network to learn the bigger data. The gradient the bigger the adjustments and vice versa. Here's where the problem lies when doing back propagation each node in a layer calculates its gradient with respect to the effects of the gradients and the layer before so the adjustments in the layer before. It is small then the adjustments in the current layer will be even smaller this cost gradients to exponentially shrink as it [36]-[40].

Back propagates down the earlier layers failed to do any learning as the internal weights are barely being adjusted due to extremely small gradient and that's the vanishing gradient problem let's see how this applies to RRN. We can think of each time step and over current no network as a layer to train an RRN [41]-[45].

Use an application of backpropagation called back propagation through time the gradients value will exponentially shrink as it propagates for each time step again the gradient is used to make the adjustments in the neural network's weights, as shown in Figure 6 , thus allowing it to learn small gradients means small adjustments. This causes the early layers to not learn because of the vanish ingredients [10][46]-[50].

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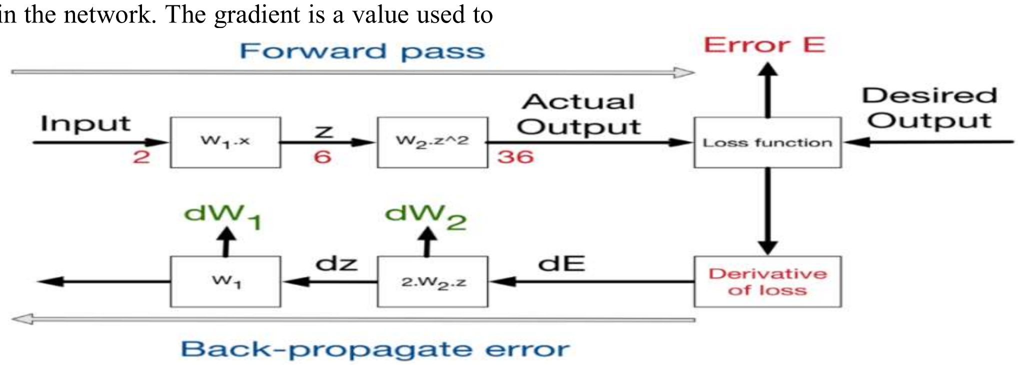

Figure 5: Forward pass and Back propagation [11]

The network tap short-term memory okay so RNN suffer from short-term memory, so how do we combat that to mitigate short-term memory to specialized recurrent neural networks were created one called long short term memory or LSTM for sure the other is gated recurrent units or use LSTM and use essentially for just like our meds, but they're capable of learning long-term dependencies using mechanism called gates these gates are different tensor operations, that can learn what information to add or remove to the hidden state because of this ability short-term memory is less of an issue for them to sum.

This up RNNs are good for processing sequence data for predictions but suffer from short-term memory the short-term memory issue for RNNs doesn't mean to skip them completely and you still more involved versions like LSTM or use RNNs have the benefit of training faster and uses less computational resources that's because there are less tensor operations to compute you could use LSTM or use when you expect a model longer sequences with long-term dependencies [12][15].

5.2 Long Short-Term Memory Networks

As a human, when you can't remember the past event at last 10 minutes, your prediction is going to be nothing better than just a random guess. Well, imagine you have the opposite problem where you can remember every word of every conversation that you've ever had [20][21].

If somebody asked you to outline your partner's wedding vows, well, you might have some trouble doing that. There's just so many words you'd need to process be much better than if you could just remember well the memorable stuff. That's where something called Long Short-Term Memory comes into play. Also abbreviated as LSTM, it allows a neural network to remember the stuff that it needs to keep hold of context, but also to forget the stuff that well is no longer applicable [22].

For example, some sequence of letters, and we need to predict what the next letter in the sequence is going to be. Just by looking at the letters individually, it's not obvious what the next sequence is, so how do we predict the sequence well, if we have gone back through the time series to look at all of the letters in the sequence. We can establish contacts and we can clearly see, and if instead of looking at letters, looked at words, we can establish that the whole sentence here [23].

RNN is really where LSTM lives, so effectively and LSTM is a type of RNN and it works in the sense that they have a node, so there's a node here and this node receives some input. We've got some input coming in. That input is then processed in some way, so there's some kind of computation and that results in and output. That's pretty standard stuff. But what makes an RNN node a little bit different is the fact that it is recurrent. That means it loops around and the output of a given step is provided alongside the input in the next step, while step one has some input.

It's processed and that results in some output. Then step two has some new input, but it also receives the output of the prior step as well. That is what makes an RNN a little bit different, and it allows it to remember previous steps in a sequence [24].

When we're looking at a sentence like ABCDE. We don't have to go back too far through those steps to Figure out what the context is, but RNN does suffer from what's known as the long-term dependency problem, which is to say that over time, as more and more information piles up, then RNNs become less effective at learning new things [25].

While we didn't have to go too far back for ABCDE as example, if we were going back through an hour's worth of clues that our murder mystery dinner, well, that's a lot more information that needs to be processed [26].

The LSTM provides a solution to this long-term dependency problem, and that is to add something called an internal state to the RNN node. Now, when an RNN input comes in, it is receiving at least state information as well. A step receives the output from the previous step, the input of the new step, and also some state information from the LSTM state.

Let's take a look at what's in there. So this is an LSTM cell and it consists of three parts. Each part is a gate. There is a forget gate. There's an input gate and there's an output gate. Now the forget gate says, what sort of state information that's stored in this internal state here can be forgotten.

It's no longer contextually relevant, the input gate says. What new information should we add or update into this working storage state information. The output gate says of all the information that's stored in that state which part of it should be output in this particular instance.

In Figure 7, we see these gates can be assigned numbers between zero and one, where zero means that the gate is effectively closed and nothing gets through, and one means the gate is wide open and everything gets through. We can say, forget everything or just forget a little bit. We can say add everything to the input state or add just a little bit and we can say output everything or just output a little bit of output, nothing at all. So now when we're processing in our RNN cell we have this additional state information that can provide us with some additional context.

If we take an example of another sentence like my name is buying apples. There's some information that we might want to store in this state. For example, X is most likely to derive to the gender of males, so we might want to stall that because that might be useful apples is a plural, so maybe we're going to store that is a plural for later on. Now, as this sentence continues to develop, it now starts to talk about new name Y. At this point, we can make some changes to our state data. We've changed subjects from X to Y.

We don't care about the gender of me anymore, so we can forget that part. And we can say the most likely gender for Nabila is female and store that instead. Really, that is how we can apply this LSTM to any sort of series where we have a sequence prediction. That's required and some long-term dependency data to go alongside of it.

Now, some, some typical use cases for using LSTM machine translation is a good one. And another one, chat bots, a Q&A chat bot where we might need to retrieve some information that was in a previous step in that chat bot and recall it later on [13][14].

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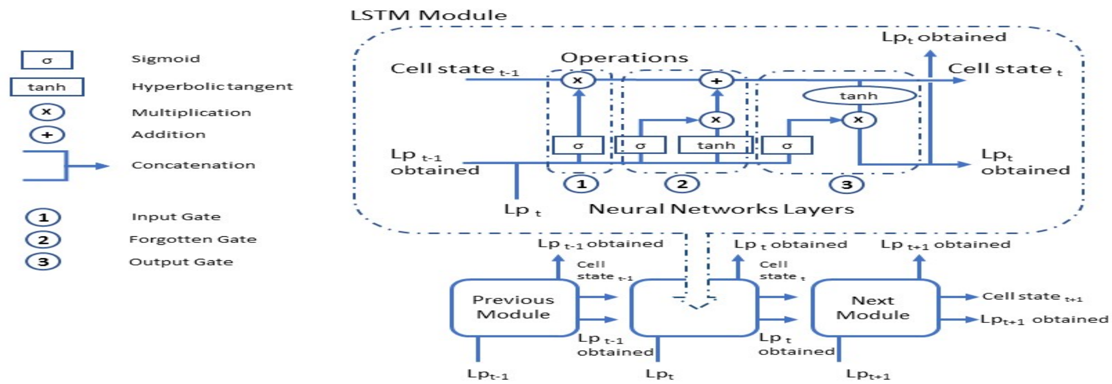

Figure 6: General scheme of an Long Short-Term Memory neural networks (LSTM) [19]

6. PREVIOUS STUDIES

In recent years, there are many studies researched on the climate change with advanced methodology as the neural network and machine learning approaches and technique. In 2020 Jonathan A. Weyn improved a model produces weather forecasts that produces weather maps patterns for months by 4-cubes map of weather prediction. It presented global weather forecasting model using convolutional neural network (CNN) to predict the atmosphere characteristics on a world map. This model includes conservative of cubed-sphere maps, the model architecture was U-met and the loss function was forced to be minimized over the prediction sequence. The cubed-sphere remaining didn't cover the world on that operations and was not provided the boundary, meanwhile the model produces weather prediction by identifying the patterns for several days. The prediction of climatology can forecast geopotential with global data for which 2-D convolutions on the cube faces, layer with U-net skip connections, with RMSE the model gave a good accuracy of prediction. They developed a machine learning algorithm that works as traditional weather models and forecasting several characteristics of weather, including temperature. But it doesn't deal with the numerical weather forecasting, it computes realistic weather predication. Model uses CNN to map the state of the atmosphere from one time to another across a 2-D maps, producing an output image of each input image area. The weights are learned by gradient back-propagation during training of the CNN of trainable parameters: their DLWP CNN has about 700,000 parameters. The dataset climatology calculated to daily from 1979 to 2010, persistence, and spectral resolution version of the earth climate maps [30].

In 2018, Deben and Bauer discussed the context of a model global climate forecasts predictions, it was developed and used to find the challenges and design choices for a predicate system based on neural networks. They developed a model based on ANNs to generate global weather predication. The model didn't use the dynamical equation of change. The model was built based longitude and latitude maps to make better predictions for the future and was competitive with predictions of other models of with shorter times, but it didn't intend to build a model that can fully make weather predictions. However, the model to identify changes and to indicate forecast systems based on ANNs. The model used for weather forecast and requires domain knowledge about the Earth system by training data and the deep understanding of how to the Earth system is working. The development of conventional models such as the complexity of the Earth system which leading to the climate predictions. However, the NNs that doesn't propagate the full atmosphere to make long-term forecasts [9].

In 2016 Iglesias et al. [13] implemented a fully connected deep neural network to forecasting the heat waves. It was trained on the time series data. They presented that neural network approach is significantly better than the linear and logistic regression. It improved the performance of forecasting the heat waves. This research shows that neural network is a good method and can be used on many climate pattern detection problem [16]. It presented how the extreme events in large datasets is a major challenge in climate algorithms based on subjective thresholds of relevant characteristics. Usually, multi-competing methods serve as different output values on the same dataset. Accurate variables of extreme events in weather simulations and observational data is important to understand the status and real impacts of such events in weather change content. This study showed an application of

Deep Learning techniques as machine learning methodology for climate extreme events detection. Deep neural networks are able to learn high-level representations of classes of patterns from labeled dataset. In that paper, they developed deep Convolutional Neural Network (CNN) classification model and presented the usefulness of Deep Learning technique for tackling weather pattern detection problems. Coupled with Bayesian based hyper-parameter optimization scheme, their deep CNN system achieves 89%-99% of accuracy in detecting extreme events (Tropical Cyclones, Atmospheric Rivers and Weather Fronts).

In this study, it used both simulations and reanalysis datasets. Detecting extreme weather patterns in simulation data we are about starting to work on satellite datasets. The reanalysis data are produced by assimilating observations into a climate dataset: CAM5.1 historical run (1979-2005), ERA-Interim reanalysis (1979-2011) and century reanalysis (1908-1948). It pulled out patterns in training data to transfer that to learning from we have, but it had problems of density estimation of modeling without more accurate even that's hence become poor of data and the neat things. The performance of Model on classifying tropical cyclones, atmospheric rivers and weather fronts was very good, but we can clearly see that the model didn't have over-fitting because of the small size of the CNN (4 layers) and the weight was normalized. Results from this study can be used for classification of extreme events but not to forecast in future climate days, in addition it works at hazard risk locations and help the policy makers 13]. In 2015, Shi et al. conducting a newly developed convolutional long short-term memory (LSTM) deep neural network to predicate the now casting. Trained maps, then the system is able to beat the current forecasting the new casting pattern. The goal of that paper is to explore that the prediction of the future rainfall in local areas over a short period of time. It had examined the challenging problem in the machine learning perspective. Climate prediction. It focused on the precipitation now casting as a time sequence prediction problem in which both the input and the forecasting target are time sequences. It used fully connected LSTM to have convolutional structures in both the input-to-state and state-to-state model, It used the convolutional LSTM (ConvLSTM) to build an end-to-end trainable model for the forecasting now casting problem. Model showed that ConvLSTM network captures spatiotemporal had better and consistently outperforms FC-LSTM and the state-of-the art the model algorithm for precipitation now casting. The Model used the rainfall prediction and acquisition to forecasting weather. It was hard for this model to give accurate predictions on the test set of the system and it is almost impossible to give full accurate forecasting of the whole radar maps in longer-term periods [27].

In 2013, Chattopadhyay et al. developed a nonlinear clustering application based on Self Organizational Map (SOM) to analysis the structure of Madden–Julian oscillation (MJO). This model didn't require selecting a leading model or intrapersonal filtering in the time and space like other models do.

This paper presented a nonlinear clustering algorithm based on a self-organizing map (SOM) model to identify horizontal and vertical structures of the Madden–Julian oscillation (MJO) through its life-cycle. The SOM description of the MJO didn't need initial patterns for selection. MJO modes are classified by SOM based on state similarities in chosen characters. New patterns of rain fall data in a supply MJO mode classified by SOM are distinct from those in other modes. The model evolution of the MJO based on SOM agrees with those from other algorithms in specific aspects and differs in others. SOM reused that the dominant longitudinal structure in the diabetic heating and related fields of the MJO is a dipole or tripole pattern with a zonal scale close to that of zones. The results showed that SOM based models is not only able to capture the gross feature in MJO formation and development, it also reveals insights that other models where they are not able to find such as the dipole and tripole formation of outgoing long wave radiation and heating in MJO [4].

Gorricha and Costa used a three-dimensional Self Organizational Map on categorizing and visualizing extreme precipitation patterns over an island in Spain. They found spatial precipitation patterns that traditional precipitation approach, and concluded that three-dimensional Self Organizational Map is very useful tool on exploratory spatial pattern study. That paper presented those extreme climate events like heavy precipitation may be analyzed from multiple variables as the daily intensity or the number of consecutive humidity days. Thus, it is necessary to get an overall view of the events in order to singular the extreme rainfall occurrence along time and land. Extreme rainfall indices, forecasted from the empirical distribution of the daily data, are increasingly being used not only to investigate ways in observed data records, but also to test the scenarios of future weather changes. However, each of the indices, by itself, shows only a part of the phenomenon and there are multiple

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factors where one single index is not enough to indicate the occurrence of extreme rainfall. Although, a hue dimensional data should be considered. In this paper, they proposed a framework for description the special patterns of extreme precipitation that is based on two types of visualization style. The first style uses linear models, like as Ordinary Kriging and Ordinary Cokriging, to produce continuous land of five extreme precipitation indices. The second style uses a three-dimensional Self Organizing Map to visualize the event from a global scene, allowing classifying of spatial patterns and homogeneous points. Also, to allow an easy interpretation of special patterns, a pattern matrix is used, where characteristic and color patterns are ordered using a one-dimensional Self-Organizing Map. The proposed framework was used to a set of indices, which were calculated using daily data from 1998 to 2000 measured at 19 meteorological stations located in Madeira Island. Results presented that the island has distinct climatic lands in relation to extreme precipitation events. The northern part of the island and the higher locations have a heavy rainfall, whereas the south and northwest parts of the island has low values in all indices. The results from this study indicated that the proposed framework, which combines linear and nonlinear style, is a valuable tool to deepen the knowledge on local special patterns of extreme rainfall [11].

7. RESEARCH GAP

All previous studies stress the importance of using AI in weather prediction because it saves time and effort with the difference in accuracy of the model, as most of the previous studies did not achieve high accuracy. Therefore, we hope our proposed model to do better than the previous studies. The studies used a dataset of images with other techniques of machine learning including CNN or LSTM, where they achieved very good accuracy, we used the RNN and LSTM with new datasets for the Prediction and got excellent that reached 100%.

Also, with reference to an important point in the Prediction process, which is the data format factor that was not considered in all previous studies compared to our work, where the time spent in the training, validation and testing was calculated.

8. METHODOLOGY

8.1 Dataset

The dataset for training, validation and testing of algorithms for Global Climate Prediction was collected form National Centers for Environmental Information website. The dataset has 27,029 Climate Data Records (.netcdf format) from 1st January 1948 to 31st December.

We used 70% of the data for training, which is equivalent to 18,920 records, and 15% for each of the testing and validation dataset, which is equivalent to 4,504 records, and each record was the daily Air Temperature all over the world disaggregated by level, latitudes and longitudes.

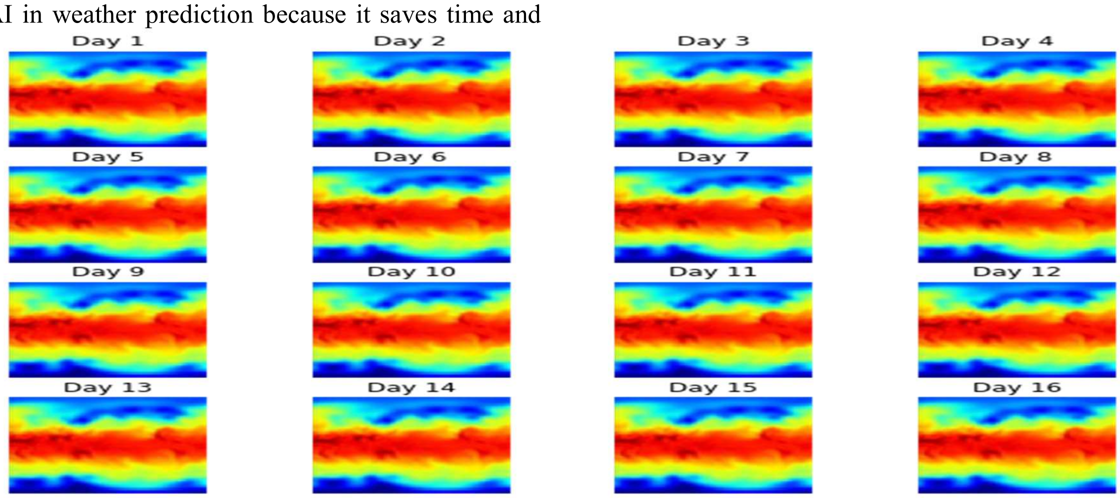

Figure 7 : Samples from Dataset (.netcdf files)

6.2 Language and tools used

Python is considered one of the most famous and most popular languages that support machine learning with the Google Colab environment, because it contains supportive libraries, is flexible, easy to use and open source, and it has the ability to train and validate very fast [51]-[55].

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We used the following libraries for developing the new proposed model:

- Pandas - Data Structure and Analysis.
- Keras - in deep learning. It wraps the efficient numerical computation libraries Theano and TensorFlow [56].
- Matplotlib - used for graphs and charts [57][58].
- Geographic Data with Basemap- used for generate the maps from netcdf data.

6.3 Network Common Data Form-netcdf Dataset

Netcdf is a data format commonly used in the scientific community to store a variety of data including model outputs. With this update database and users can share visualize and download netcdf files within the system and files are identified by the netcdf extension. The netcdf dataset represents model temperature values over a span of time. The import process for netcdf data is very similar to that for layer packages with one extra step. First, we need to provide some basic information about the dataset such as its X&Y dimensions projection temporal information and how to render it for this application. We used the original data to represent temperature and specify some basic temporal information so that we can use the time slider in the map. The remainder of the import process is the same as it is for layer packaged imports. We filled out the basic required fields and hit submit once the import completes. We brought to the dataset then we see that is a netcdf dataset and that time enabled.

We can download the data or view it in the live map viewer netcdf dataset.

6.4 Network Architecture

In Figure 9, the Model Architecture which contains from 6 layers and Input layer

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, None, 72, 144, 1  0
                             )]

 conv_lstm2d_1 (ConvLSTM2D)  (None, None, 72, 144, 64  416256
                             )

 batch_normalization (BatchN  (None, None, 72, 144, 64  256
 ormalization)               )

 conv_lstm2d_2 (ConvLSTM2D)  (None, None, 72, 144, 64  295168
                             )

 batch_normalization_1 (Batc  (None, None, 72, 144, 64  256
 hNormalization)             )

 conv_lstm2d_3 (ConvLSTM2D)  (None, None, 72, 144, 64  33024
                             )

 conv3d (Conv3D)             (None, None, 72, 144, 1)  1729

=================================================================
Total params: 746,689
Trainable params: 746,433
Non-trainable params: 256
_________________________________________________________________
```

Figure 9: Model Architecture

In the Figure 10, we illustrate the last 20 epochs of the training and validation of the proposed model.

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```
Epoch 1/20
180/180 [==============================] - 179s 953ms/step - loss: 0.0108 - acc: 0.9930 - val_loss: 0.0416 - val_acc: 1.0000 - lr: 0.0010
Epoch 2/20
180/180 [==============================] - 171s 947ms/step - loss: 2.4113e-07 - acc: 1.0000 - val_loss: 0.0028 - val_acc: 1.0000 - lr: 0.0010
Epoch 3/20
180/180 [==============================] - 171s 948ms/step - loss: 1.3554e-07 - acc: 1.0000 - val_loss: 2.3897e-05 - val_acc: 1.0000 - lr: 0.0010
Epoch 4/20
180/180 [==============================] - 171s 948ms/step - loss: 8.3074e-08 - acc: 1.0000 - val_loss: 3.6590e-07 - val_acc: 1.0000 - lr: 0.0010
Epoch 5/20
180/180 [==============================] - 171s 948ms/step - loss: 5.2976e-08 - acc: 1.0000 - val_loss: 7.5184e-08 - val_acc: 1.0000 - lr: 0.0010
Epoch 6/20
180/180 [==============================] - 171s 947ms/step - loss: 3.7445e-08 - acc: 1.0000 - val_loss: 4.1064e-08 - val_acc: 1.0000 - lr: 0.0010
Epoch 7/20
180/180 [==============================] - 170s 947ms/step - loss: 2.8650e-08 - acc: 1.0000 - val_loss: 2.9400e-08 - val_acc: 1.0000 - lr: 0.0010
Epoch 8/20
180/180 [==============================] - 170s 947ms/step - loss: 2.3079e-08 - acc: 1.0000 - val_loss: 2.3254e-08 - val_acc: 1.0000 - lr: 0.0010
Epoch 9/20
180/180 [==============================] - 171s 948ms/step - loss: 2.0662e-08 - acc: 1.0000 - val_loss: 2.1012e-08 - val_acc: 1.0000 - lr: 1.0000e-04
Epoch 10/20
180/180 [==============================] - 171s 948ms/step - loss: 2.0254e-08 - acc: 1.0000 - val_loss: 2.0305e-08 - val_acc: 1.0000 - lr: 1.0000e-04
Epoch 11/20
180/180 [==============================] - 170s 947ms/step - loss: 1.9816e-08 - acc: 1.0000 - val_loss: 1.9816e-08 - val_acc: 1.0000 - lr: 1.0000e-04
Epoch 12/20
180/180 [==============================] - 170s 947ms/step - loss: 1.9355e-08 - acc: 1.0000 - val_loss: 1.9346e-08 - val_acc: 1.0000 - lr: 1.0000e-04
Epoch 13/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8875e-08 - acc: 1.0000 - val_loss: 1.8862e-08 - val_acc: 1.0000 - lr: 1.0000e-04
Epoch 14/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8604e-08 - acc: 1.0000 - val_loss: 1.8639e-08 - val_acc: 1.0000 - lr: 1.0000e-05
Epoch 15/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8556e-08 - acc: 1.0000 - val_loss: 1.8561e-08 - val_acc: 1.0000 - lr: 1.0000e-05
Epoch 16/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8503e-08 - acc: 1.0000 - val_loss: 1.8503e-08 - val_acc: 1.0000 - lr: 1.0000e-05
Epoch 17/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8445e-08 - acc: 1.0000 - val_loss: 1.8444e-08 - val_acc: 1.0000 - lr: 1.0000e-05
Epoch 18/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8382e-08 - acc: 1.0000 - val_loss: 1.8380e-08 - val_acc: 1.0000 - lr: 1.0000e-05
Epoch 19/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8345e-08 - acc: 1.0000 - val_loss: 1.8350e-08 - val_acc: 1.0000 - lr: 1.0000e-06
Epoch 20/20
180/180 [==============================] - 170s 947ms/step - loss: 1.8340e-08 - acc: 1.0000 - val_loss: 1.8340e-08 - val_acc: 1.0000 - lr: 1.0000e-06
```

Figure 10: The model starts training and logs the loss and accuracy

While training the model, the loss and accuracy metrics are shown. This model achieves training accuracy of about 100% and training loss is 0.0.

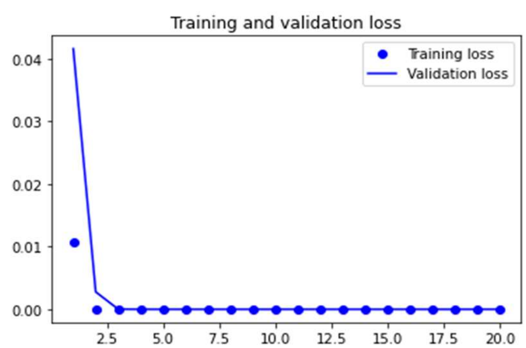

Figure 8: Training and Validation Loss, 20 epochs

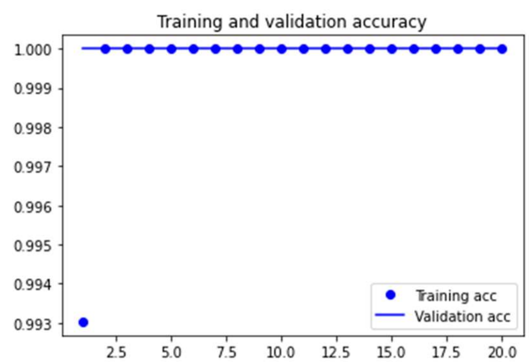

Figure 9: Training and Validation Accuracy, 20 epochs

During the training of the model the loss and accuracy values are recorded, and a validation dataset was used to check the performance of the model. Also, "Matplotlib" was used to draw a chart showing the tracking of the results of the training and validation process in terms of loss and accuracy, as shown in the Figure 11 and Figure 12.

We notice that the loss of validation and training of decreases with each iteration, and this is a good thing, and it gives us an indication that the model achieves its goals. On the other hand, it appears that the validation accuracy of the model increases to reach 100%, which is an excellent percentage.

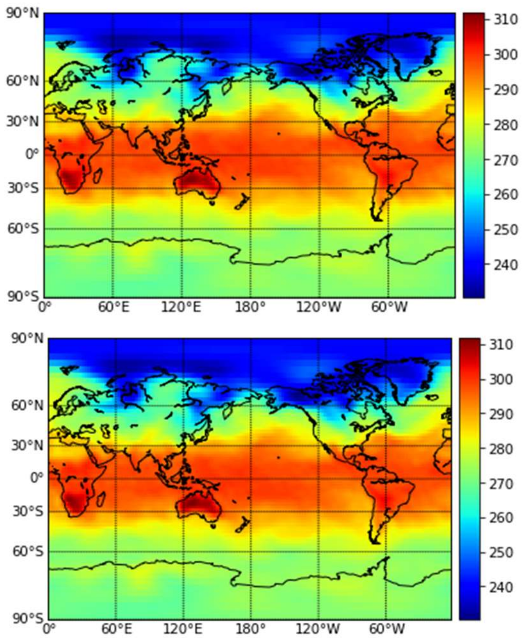

Figure 13: Comparison between real maps and predicated maps

7. CONCLUSION

This research presents a significantly Climate forecasting model using a deep convolutional Long Short-Term Memory (LSTM) to forecast temperatures world widely. New developments in this model include the next-days prediction with Convolutional LSTMs mapping of past climate change to project future climate change since the observed changes. In addition, the model of unsupervised Deep Learning networks is for tackling climate patterns detection problems and the improvements Recurrent Neural Network-RNN architecture by minimization the loss function over multiple sequence steps. Our model is considered one of the best models comparing with others, due to its high testing accuracy (100%).

The results were summarized by displaying them in tables for ease of comparison in terms of accuracy and loss. Because the amount of data used is large, the Batch normalization technique was used in order to obtain higher accuracy.

We got similar results for dataset, but using the netcdf dataset and our model gave the highest accuracy rate of 100%.

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