CLIMATE CHANGE

TEAM NAME: Team X

TEAM NUMBER: Team 8

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Introduction

Climate is the long-term weather pattern in an area, typically averaged over 30 years.

Climate change refers to long-term shifts in temperatures and weather patterns. These shifts may be natural, such as through variations in the solar cycle. But since the 1800s, human activities have been the main driver of climate change, primarily due to burning fossil fuels like coal, oil, and gas.

Earth's climate is undergoing changes never seen before by humans. Compared with levels before the Industrial Revolution, the global average temperature has risen a full degree Celsius. That may not sound like much, but it's already severely impacted how our planet functions.

Studying climate change will help us understand why global temperatures continue to rise, how the climate affects us, and how we can tackle this challenge before things get much worse.

Effects of Climate Change

Left unchecked, climate change has the potential to:

- Increase the frequency of natural disasters.
- Damage natural ecosystems and human-built infrastructures.
- Cause human health issues via food shortages, increased heat, pollution, and more.

Any change that affects the planet ultimately affects human beings. The only way to help reduce the change is to stay educated and informed about climate change. After all, **we caused it, so it's up to us to stop it.**

Our Objectives:

- Analysis of global temperature trends over two centuries.
- Spatial analysis of Global temperature change.
- Effect of temperature on rainfall.

- Analysis of major events on temperature.
- Correlation of CO_2 emissions with temperature change.
- To predict the future temperature(single and Multi-Step).

Methods

Global Temperature Analysis

- Took the monthly data for a year and got the mean for that year. We did this for many years. We plotted the values which I got vs. years using a line plot.
- For intervals of 10 years, take the difference between last year's average and the first-year average as the rate of change of temperature.

Spatial Analysis

- For the highest-temperature cities and countries just took the average temperature difference for the years 1910 and 2010 and sorted them according to the difference.
- For plotting the map, We used the folium library. The data used was the country's name and temperature difference.

Rainfall Analysis

- We tried to see the correlation between Annual Rainfall and Average annual temperature in different states of India between 1900-2013.
- We also analyzed the percent change in Average Annual Rainfall and Average Annual Temperature between 1900-1920 and 1990-2010.

Event Analysis

Here, we look for the effects on average global or local temperatures by some significant events throughout history.

- For each event, we look at the temperatures for 25 to 50 years before and after. We look at the average change in temperature per year for those periods.
- For example, in the case of the Chandrapur power plant, which started running in the year 1984, we first find the average change in temperature of the district in the period 1965-1984 (before the start of the power plant), and we also find the average change in temperature of the district in the period 1984-2014 (after starting of the power plant). Thus, we compare the average change in temperature before and after the event.
- To find the average change in temperature during a period, we fit a line on the average temperature per year data, and its slope is the average change during that period.

Correlation of CO2 emission with temperature

We look at the yearly average temperatures of the countries and find the Pearson Correlation Coefficient between the yearly CO2 emission and yearly average temperatures. (Pearson Correlation Coefficient measures the linear correlation between two sets of data)

Temperature Forecasting

Used only one feature called AverageTemperature to forecast the temperature. The dataset contains the monthly data from 1743 to 2013.

Temperature Forecasting is covered in two main parts:-

- Forecast for a single time step:
  - Using only a single timestep
  - Using multiple timesteps
- Forecast multiple steps:
  - Single-shot: Make the predictions all at once.
  - Autoregressive: Make one prediction at a time and feed the output back to the model.
- Normalizing the data**:** It is important to scale features before training a neural network. Normalization is a common way of doing this scaling: subtract the mean and divide it by the standard deviation of each feature. The mean and standard deviation should only be computed using the training data so that the models cannot access the values in the validation and test sets.
- After Normalizing the data, we split it into training, validation, and test data.
- We will use a (70%, 10%, and 10%) split for the training, validation, and test sets.

Forecasting for Single-step models:- It means that we have to forecast the temperature of one time step(one month) into the future based only on the current conditions. We use the following models:

- **Baseline Model**: Before building a trainable model, it would be good to have a performance baseline as a point for comparison with the later more complicated models. This first task is to predict temperature one hour into the future, given the current value of all features. The current values include the current temperature. So, start with a model that returns the current temperature as the prediction, predicting "No change."
- **Linear model:** The simplest trainable model you can apply to this task is to insert a linear transformation between the input and output. In this case, the output from a time step only depends on that step.
- **Dense:** Before applying models that actually operate on multiple time steps, it's worth checking the performance of deeper, more powerful, single-input step models. Here's a model similar to the linear model, except it stacks several Dense layers between the input and the output.

- **Multi-step dense:** A single-time-step model has no context for the current values of its inputs. It can't see how the input features are changing over time. To address this issue, the model needs access to multiple time steps when making predictions.Use a 2 layer Neural network.
- **Convolution Neural Network:** Instead of using Multilayer Perceptron(MLP) in the model, we can use convolution, which will take fewer parameters than MLP. Here we have used one layer of convolution with 256 numbers filters.
- **LSTM:** A Recurrent Neural Network (RNN) is a type of neural network well-suited to time series data. RNNs process a time series step-by-step, maintaining an internal state from time to time.

Multi-Step Forecasting: In a multi-step prediction, the model needs to learn to predict a range of future values. Thus, unlike a single-step model, where only a single future point is predicted, a multi-step model predicts a sequence of future values.

There are two rough approaches to this:

1. Single shot predictions where the entire time series is predicted at once.
2. Autoregressive predictions, where the model only makes single-step predictions, and its output is fed back as its input.

For the multi-step model, the training data again consists of hourly samples. However, here, the models will learn to predict 24 hours into the future. We use the following models:

- **Last:** A simple baseline for this task is to repeat the last input time step for the required number of output time steps.
- **Repeat:** Since this task is to predict 24 hours into the future, given 24 hours of the past, another simple approach is to repeat the previous day, assuming tomorrow will be similar.
- **Linear:** We use the last time step only to predict all the step outputs.
- **Dense:** Same Model as the linear model, just uses a deep neural network to get all the step outputs.
- **Convolutions:** Here, Use the previous 24 Months of the data and use a convolution operator on those to learn the structure of the data.
- **LSTM:** A LSTM model can learn to use a long history of inputs if it's relevant to the predictions the model makes. Here the model will accumulate an internal state for 24 hours before making a single prediction for the next 24 hours. In this single-shot format, the LSTM only needs to produce an output at the last time step.
- **Auto Regressive LSTM (AR-LSTM):** The above models predict the entire output sequence in a single step. In some cases, it may be helpful for the model to decompose this prediction into individual time steps. Then, each model's output can be fed into itself at each step, and predictions can be conditioned on the previous one. One clear advantage to this model style is that it can be set up to produce output with a varying length, and also, at the time of prediction of i^{th} the time step, we can use the output generated till $(i-1)^{th}$ time step.

Results

Global Temperature Analysis

To understand the global temperature trend we took the global land temperature average for each year from 1780 and plotted that with each year's temperature. The result is as show below:

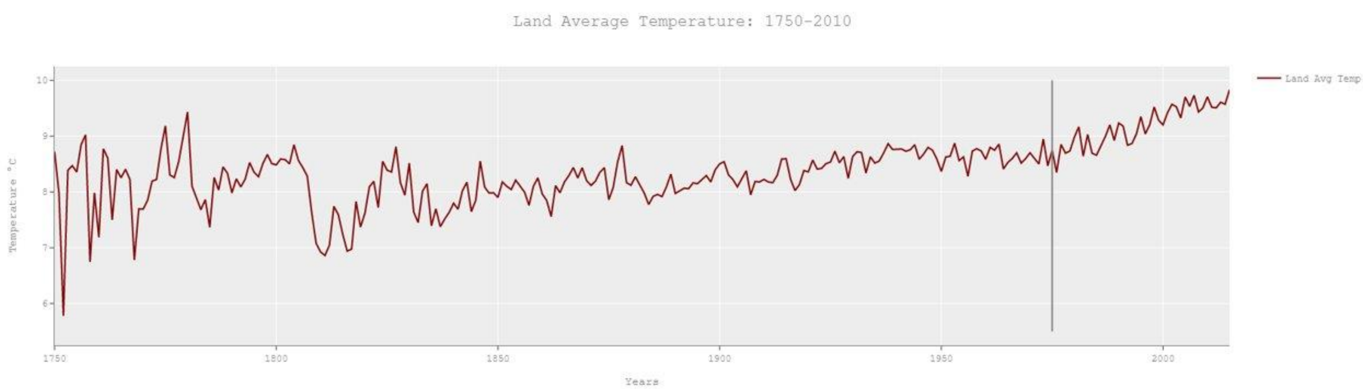


Figure 1: Global average temperature

Here in the above image, we can see the global average rise in the land temperature. Until 1975 it was not rising so significantly, but after that, we can see a steady rise in the temperature.

After this, we tried to look at the rate of increase in temperature per decade globally for land and land-ocean temperature collectively. The results we got are given below:

- Average rate of increase in temperature of **land** from 1980 per decade is **0.39**°C(0.70°F)
- Average rate of increase in temperature of **land** from 1880 per decade is **0.14**°C(0.25°F)

- Average rate of increase in temperature of **land & ocean** from 1980 per decade is **0.23**°C(0.41°F)
- Average rate of increase in temperature of **land & ocean** from 1880 per decade is **0.08**°C(0.14°F)

According to the above results the combined land and ocean temperature has increased at an average rate of 0.081 degrees Celsius per decade since 1880; however, the average rate of increase since 1981 is (0.23°C / 0.32°F) has been more than **twice** that rate.

Table 1	
Country	ΔT
Jordan	3.253250
Iraq	3.228208
Israel	3.176407
Syria	3.098238
Iran	3.097646
Egypt	3.052908
Lebanon	2.980083
Armenia	2.977833
Georgia	2.977833
Bahrain	2.840583

Table 2	
City	ΔT
Srinagar	1.478167
Pathankot	1.372583
Jammu	1.372583
Ludhiana	1.336917
Phagwara	1.336917
Khanna	1.336917
Amritsar	1.336917
Jalandhar	1.336917
Hoshiarpur	1.336917
Firozpur	1.336917

Table 3	
Country	ΔT
Sweden	-1.444583
Norway	-1.413125
Denmark	-1.356417
Finland	-1.270350
Estonia	-1.034167
Lithuania	-0.858733
Latvia	-0.742500
Netherlands	-0.609014
Poland	-0.557682
Germany	-0.395712

- In **Table 1,** we tried to look at the countries where the difference in change of temperature was the highest or we can say that countries highly affected by global warming.
- In **Table 2,** we tried to look at the Indian cities where the difference in change of temperature was the highest.
- In **Table 3,** we looked for countries where the change in temperature was minimum globally.

Coincidentally these places also match as the best places to live in the world.
The same thing we tried to plot on a world map. The image is in figure 2.

In figure 2, darker regions represent more change in temperature compared to lighter ones. We can see that most European countries are least affected by global warming compared to the rest of the world.

Rainfall Analysis

Correlation between Rainfall and Temperature

We studied the correlation between Annual Temperature and Rainfall for various states of India from 1901 to 2013. The result is shown in figure 3,

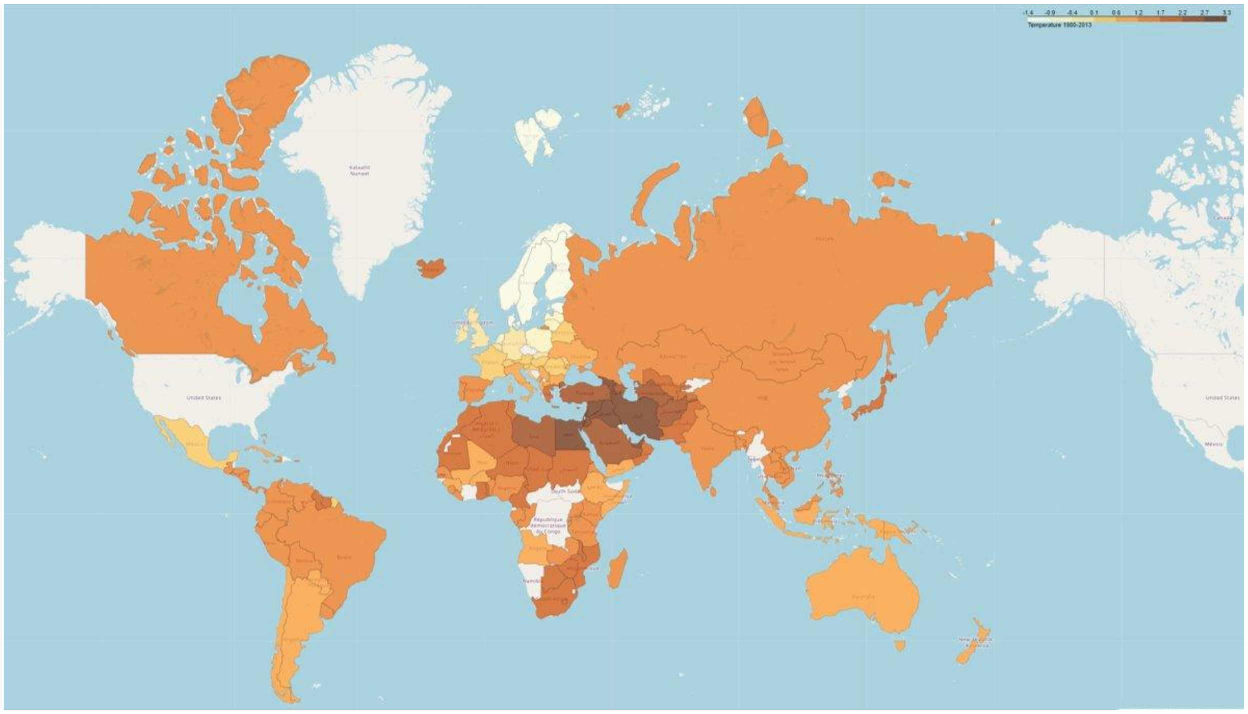


Figure 2: Change in average temperature over a century

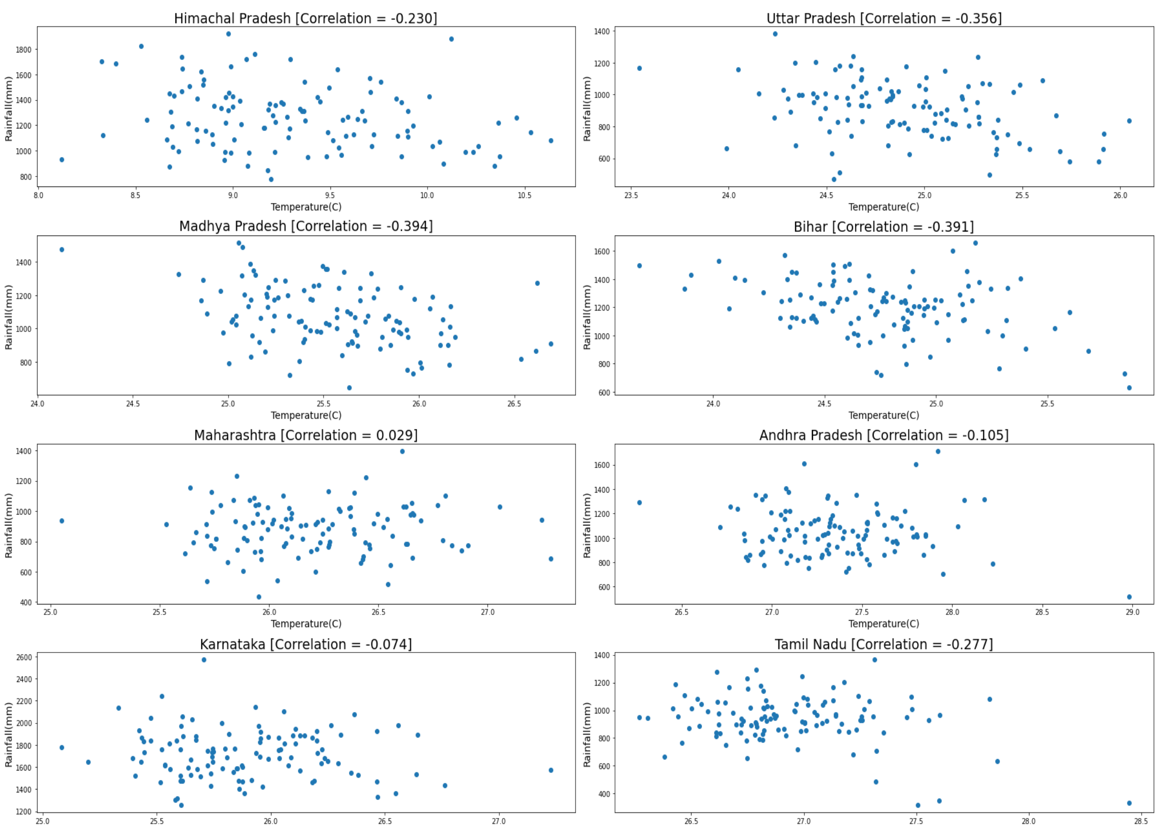


Figure 3: Correlation between temperature and rainfall for some Indian states

We observed that there is not any strongly negative or positive correlation between annual rainfall and average annual temperature. In north India such as Uttar Pradesh, Madhya Pradesh, and Bihar negative correlation is slightly higher compared to south India.

Percent Change in Rainfall and Temperature over time

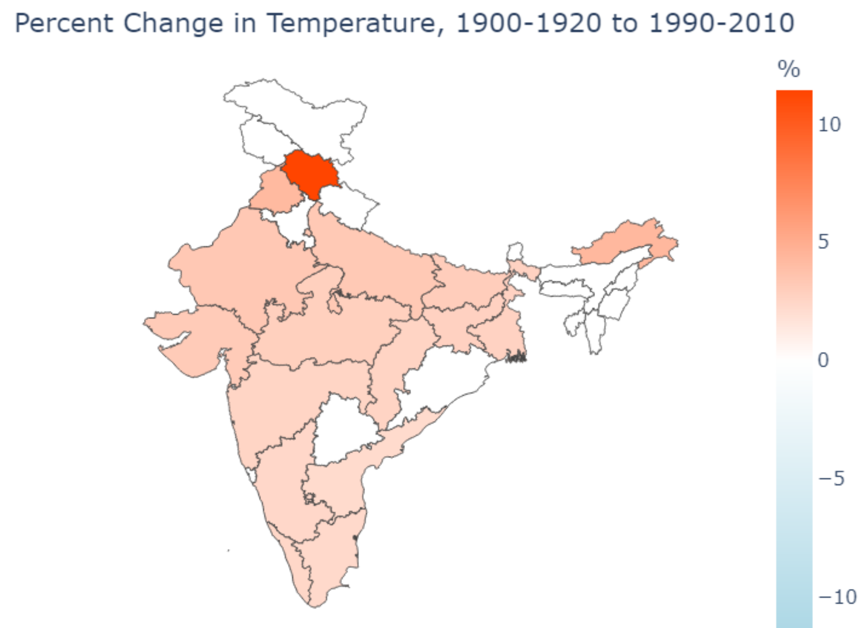


Figure 4: Change in temperatures of Indian states

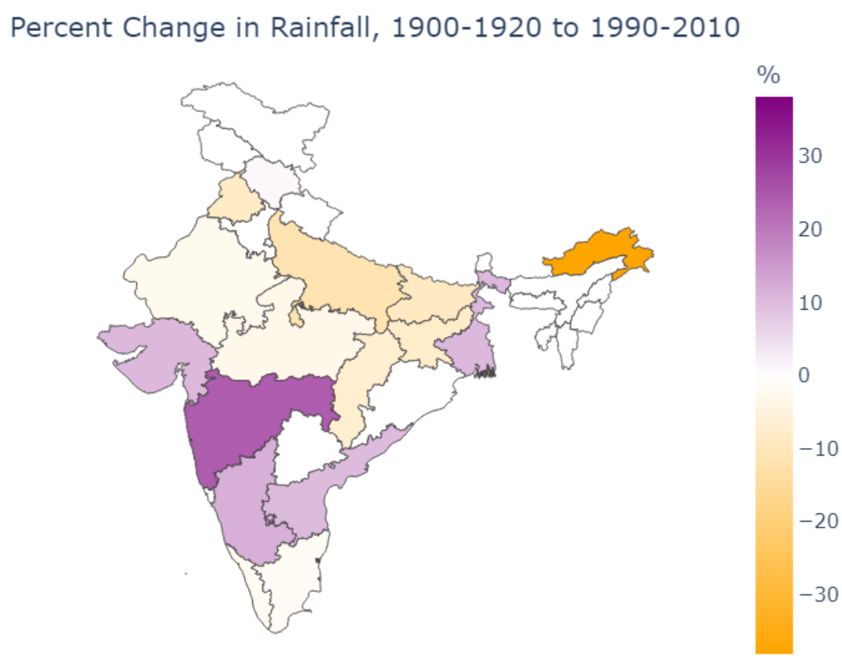


Figure 5: Change in rainfall of Indian states

From figure 4 we can see that in every state temperature has risen by 2% to 5% except for Himachal Pradesh where the temperature has risen by 11%.

From figure 5 we can see that the Average Annual Rainfall has increased in some states such as Maharashtra, Andhra Pradesh, Karnataka, etc. On the other hand, Rainfall has decreased in northern states such as Uttar Pradesh, Bihar, Madhya Pradesh, etc.

Event Analysis

2nd industrial revolution

The Second Industrial Revolution, also known as the Technological Revolution, was a phase of rapid scientific discovery, standardization, mass production, and industrialization from the late 19th century into the early 20th century (1870 - 1915).

We looked at the global average temperatures before, during, and after the 2nd industrial revolution.

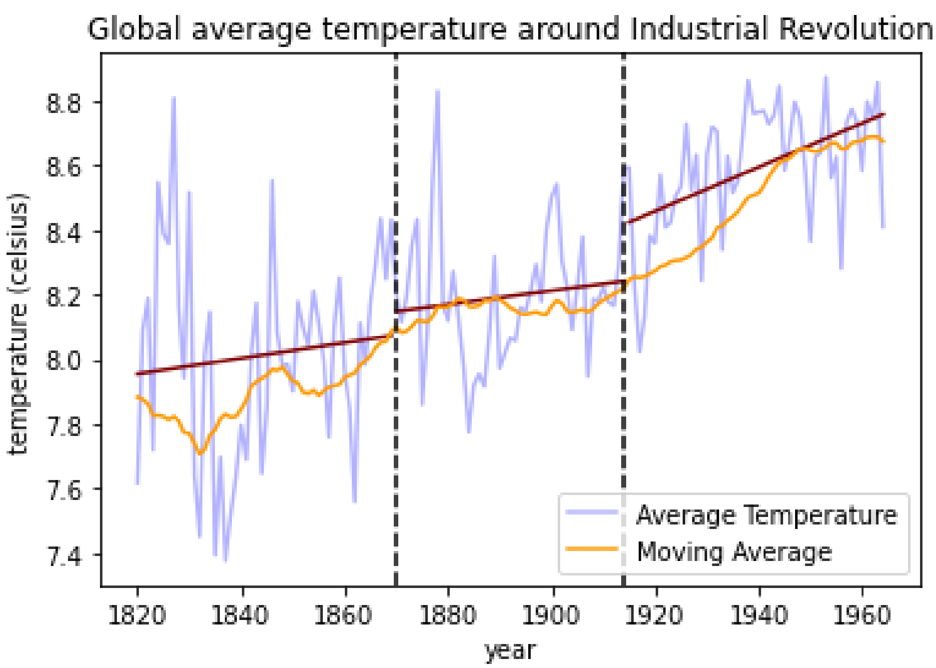


Figure 6: Global temperature around the industrial revolution

The average increase in Global temperatures per year are:

- Before 1870: 0.0024 ºC per year
- 1870 - 1915: 0.0021 ºC per year
- After 1915: 0.0068 ºC per year

Hiroshima Bombing

The United States detonated two atomic bombs over the Japanese cities of Hiroshima and Nagasaki on 6 and 9 August 1945, respectively. The two bombings killed between 129,000 and 226,000 people.

We look at the change in the average temperature of the city of Hiroshima before and after the bombings.

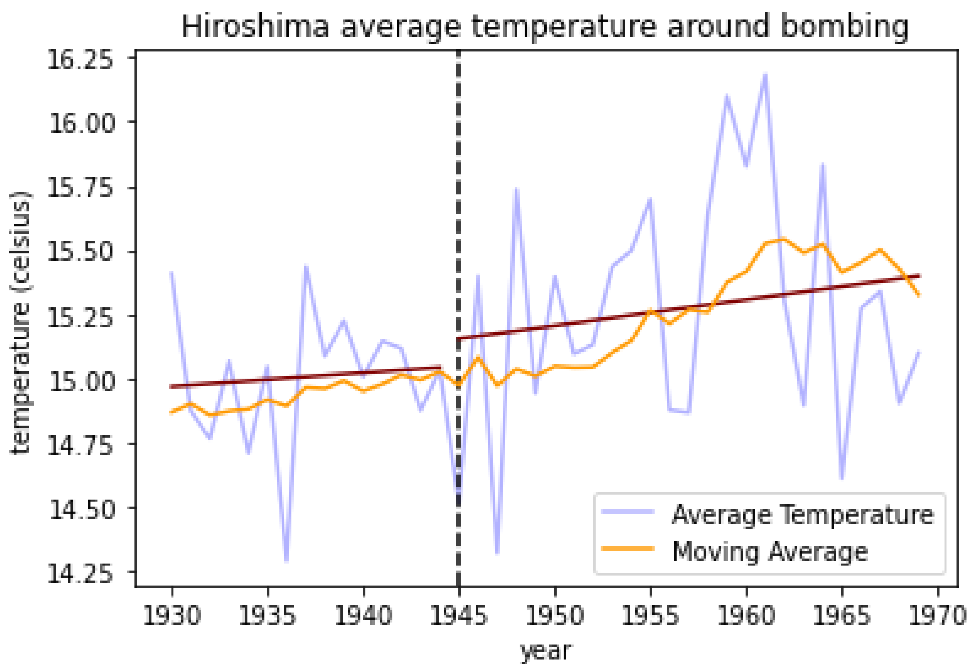


Figure 7: Temperature of Hiroshima around the bombing

The average increase in Hiroshima temperatures per year are:

- Before 1945: 0.0052 ºC per year
- After 1945: 0.0101 ºC per year

Launch of Ford Model T

The Ford Model T was named the most influential car of the 20th century in 1999. With 15 million sold, it was the most sold car in history before being surpassed by the Volkswagen Beetle in 1972.

We look at the average temperature of the United States before and after the launch of Model T. It is the period when the country experienced a car boom.

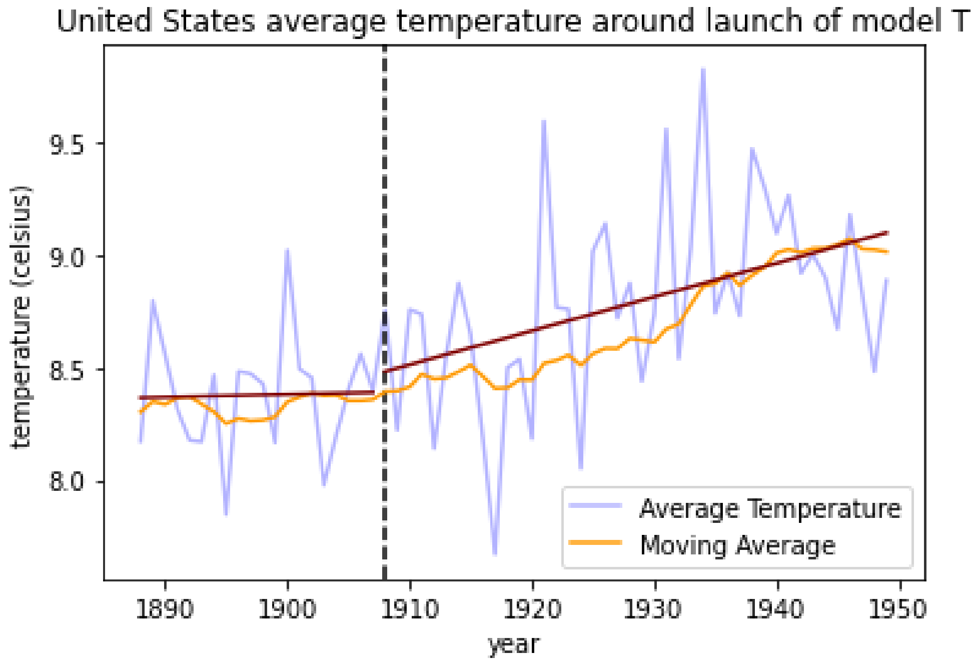


Figure 8: Temperature of The United States around the launch of Model T

The average increase in the United States temperatures per year are:

- Before 1908: 0.0012 °C per year
- After 1908: 0.0150 °C per year

Chandrapur Power Plant

Chandrapur Super Thermal Power Station (often abbreviated as CSTPS) is a thermal power plant located in Chandrapur district in the Indian state of Maharashtra. The power plant is one of the coal-based power plants of MAHAGENCO. With a total capacity of 3340MW, the plant is the largest power plant in Maharashtra. It accounts for more than 25% of Maharashtra's total needs.

We look at the average temperatures of the district before and after the start of the power plant.

The average increase in Chandrapur temperatures per year is:

- Before 1984: 0.0079 °C per year
- After 1984: 0.0224 °C per year

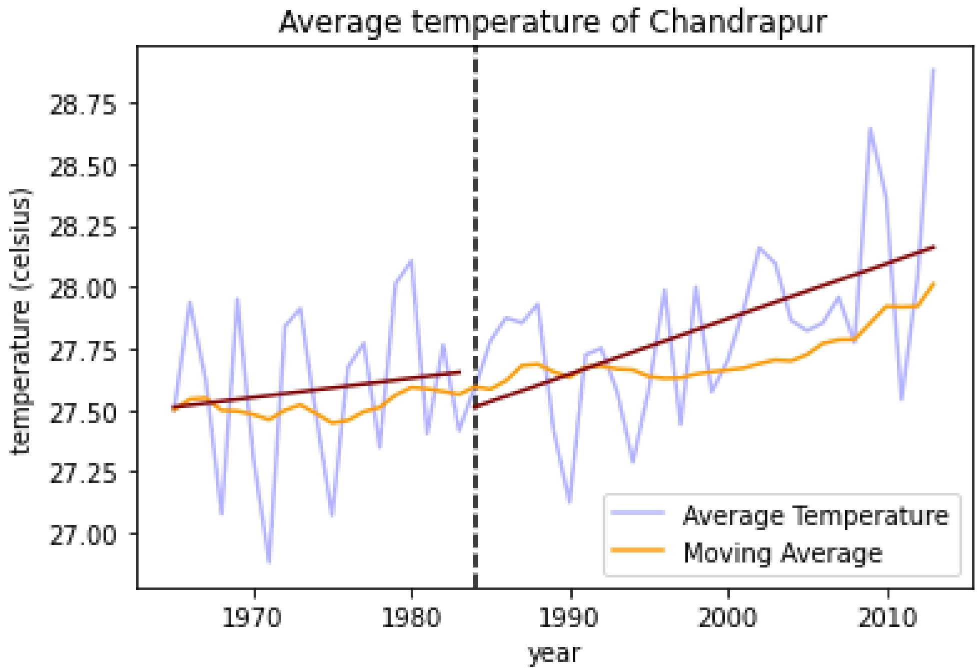
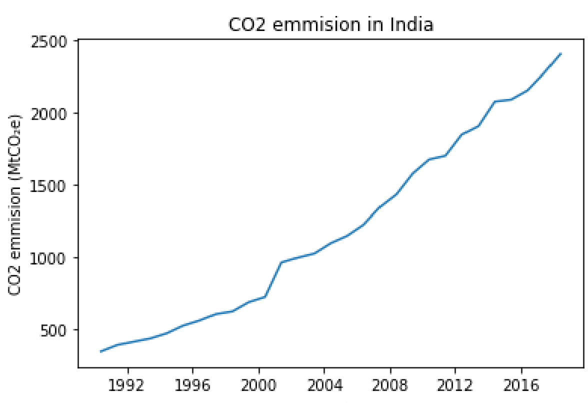


Figure 9: Temperature of Chandrapur around commissioning of power plant

Correlation of CO2 emission with temperature

We look at two countries to find the correlation of CO2 emission with average temperatures. One country where CO2 emission increased with time and one where it decreased.

India



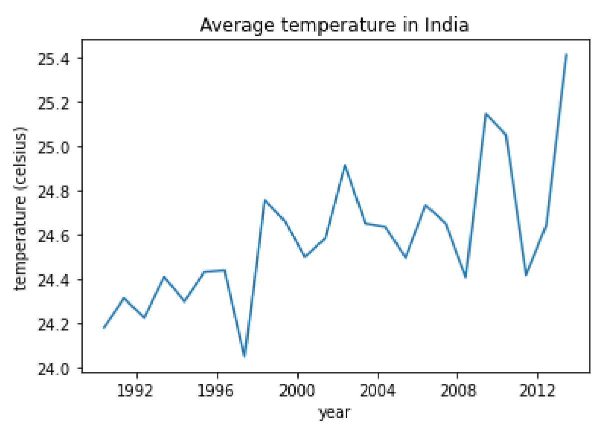


Figure 10: CO2 emission and temperatures of India

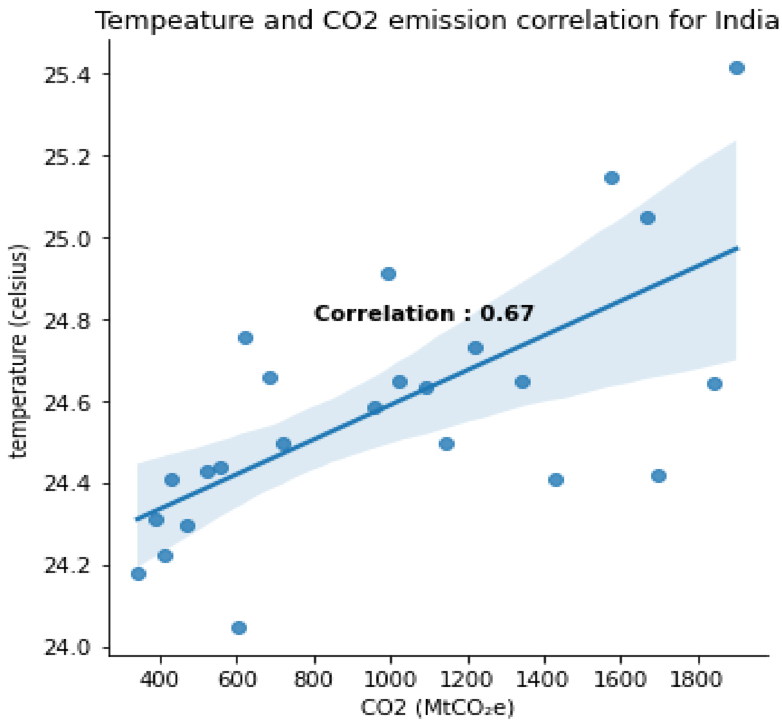


Figure 11: Correlation between temperature and CO2 emission in India

For India, where CO2 emission increased, there is a good positive correlation with the average temperature.

Germany

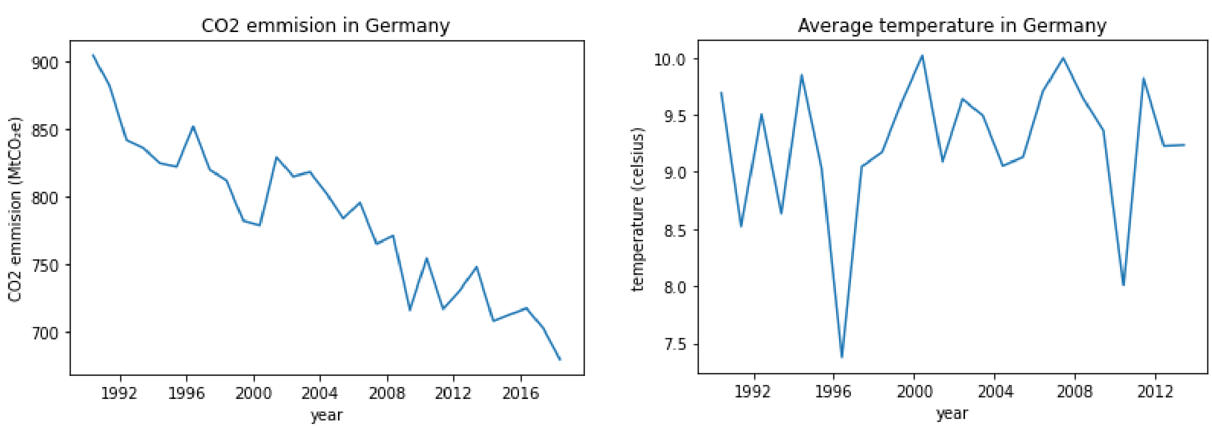


Figure 12: CO2 emission and temperatures of Germany

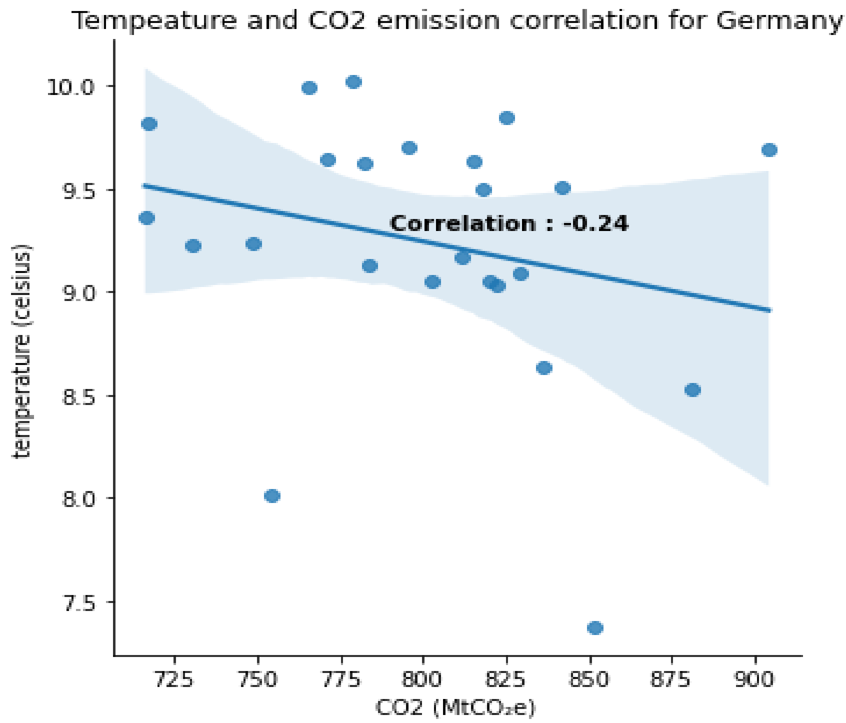


Figure 13: Correlation between temperature and CO2 emission in Germany

For Germany, where CO2 emission decreased over time, there is a weak negative correlation with average temperature.

One observation in the case of Germany, where the CO2 emission has decreased is that there is almost no rise in the average temperatures. Whereas in the case of India, the temperature is increasing over time.

Temperature Forecasting:

The Metric that has been used is Mean Absolute Error. The Plot of the validation and test set is given in figure 14.

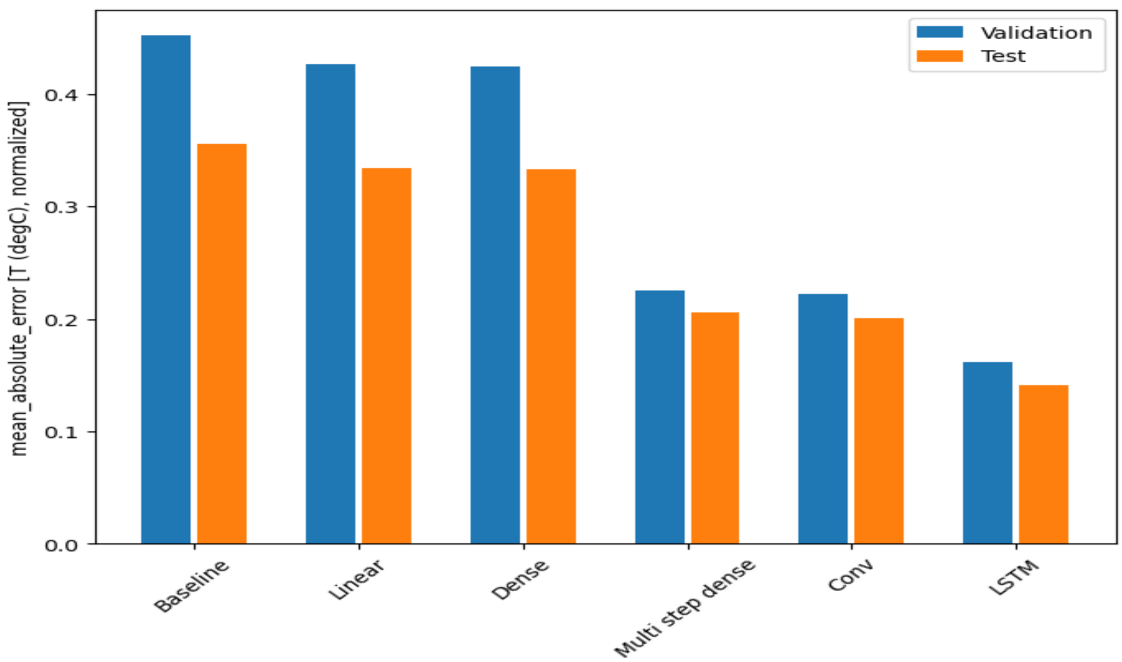


Figure 14: Errors for single step forecasting

In the test Data the error we are getting MAE as-

Model Used	**MAE(mean absolute Error) on test data**
BaseLine	0.36
Linear	0.33
Dense	0.32
MultiStep Dense	0.2057
Convolution	0.19
LSTM	0.14

Table 4: MAE on test data for single step forecasting

Observation:- Since Baseline, linear and dense all the models are taking only one input for predicting the output. So the models cannot learn how the input features change over time. Whereas the other Models, like Multistep Dense, Convolution, and LSTM, can access multiple time steps when making predictions, we can see from the plots and the tables that these models are performing better than the previous three models. And even in these models, LSTM is performing better because, with the help of LSTM, we can consider long-term dependency.

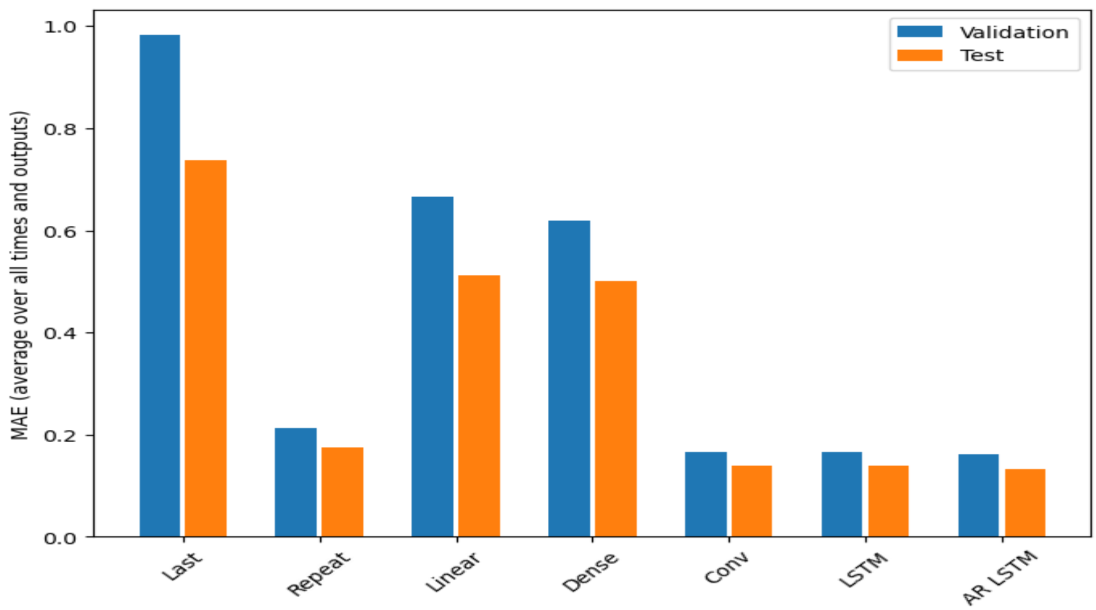


Figure 16: Temperature of Chandrapur around commissioning of power plant

In the test Data the error we are getting MAE for multistep Models are

Models Used	**MAE(Mean Absolute Error) on test data**
LAST	0.7378
Repeat	0.19
Linear	0.46
Dense	0.44
Convolution	0.17
LSTM	0.14
AR-LSTM	0.13

Table 5: MAE on test data for multi-step Models

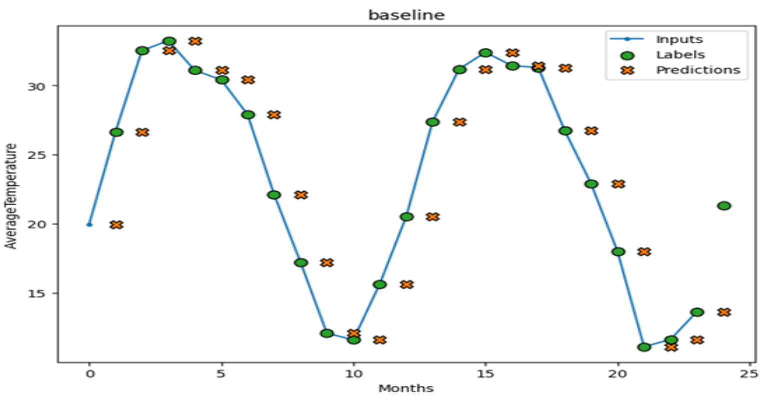
Observations:- Out of the two Baseline Model, we have seen that the repeat Baseline is performing better than a linear and dense model since they are only considering one of the inputs. The repeat baseline is performing better than them. To beat the baseline, I used convolution, LSTM, and AR-LSTM.
And again, from the numbers, we can infer that AR-LSTM is performing slightly better than all the other models because even when you are predicting all the time steps. Then, each model's

output can be fed back into itself at each step, and predictions can be made conditioned on the previous one, unlike the previous 2 models (LSTM and Convolution).

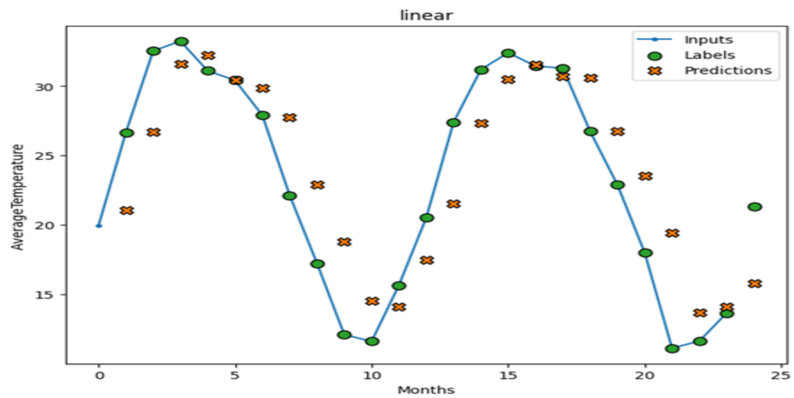
Inference:-

We have taken Abohar city data from 1816-03-01 to 1818-02-01.I have seen the Variation in the average temperature for Abohar city.

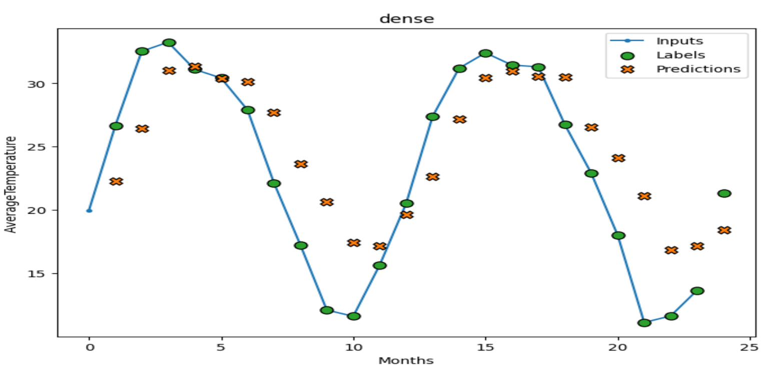
Single Step Models:



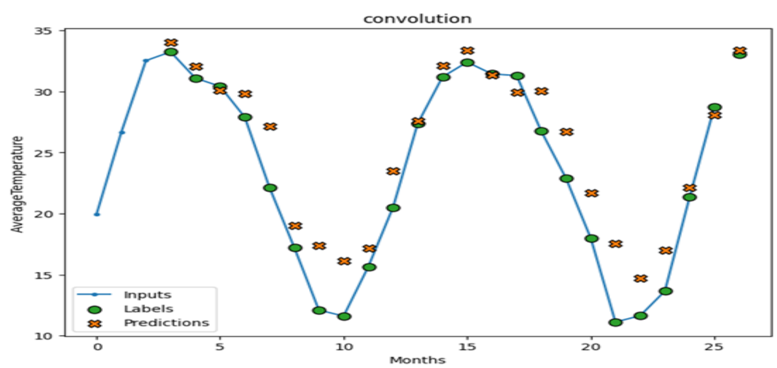
Baseline



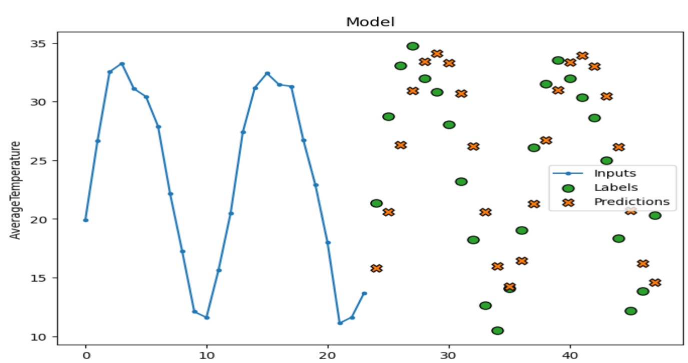
Linear



Dense



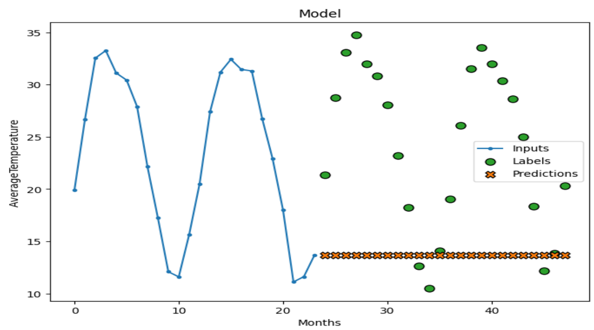
Convolution



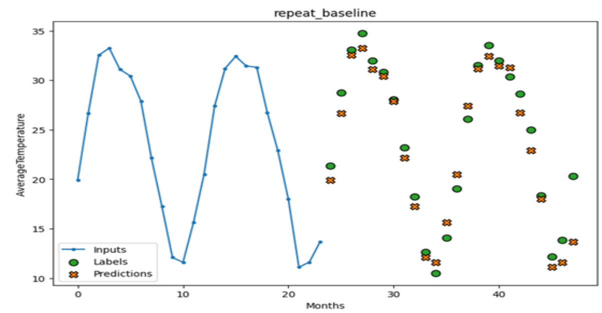
LSTM

Figure 17: Single step models inference

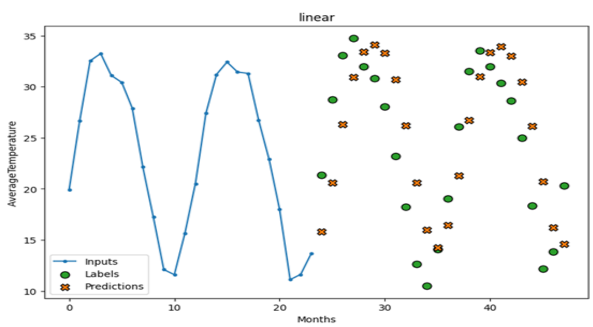
MultiStep Models:



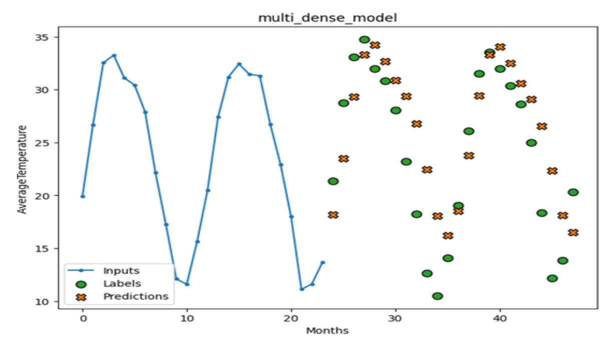
Last Model



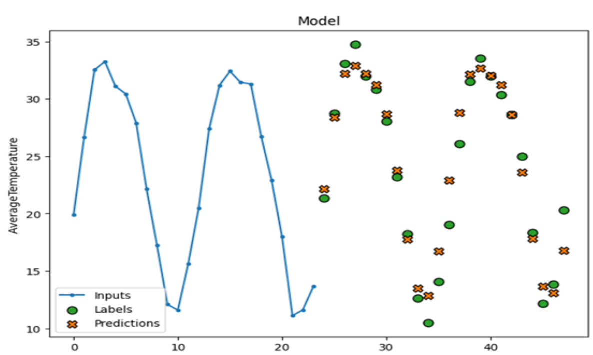
Repeat Model



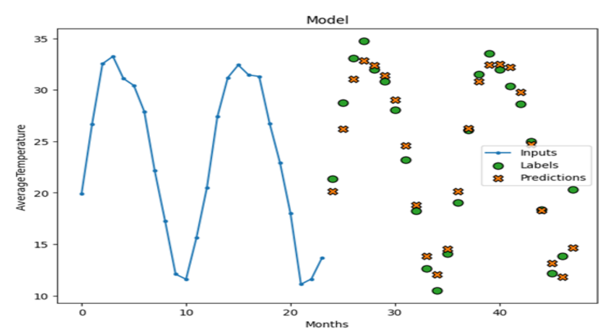
Linear Model



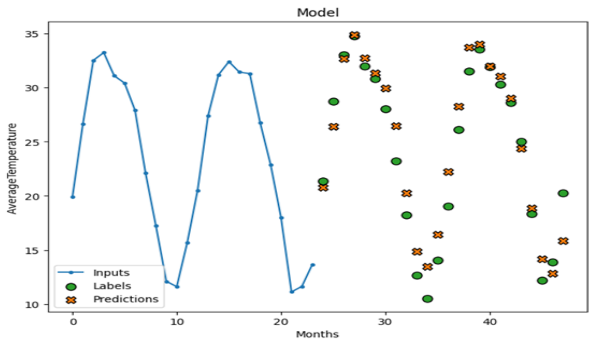
Multidense Model



Convolution Model



LSTM Model



AR-LSTM

Figure 18: Multi-step models inference

Conclusion

There is still time to avoid the worst impacts of climate change if we take strong action now.

Climate change will affect the essential elements of life for people around the world – access to water, food production, health, and the environment. Hundreds of millions of people could suffer hunger, water shortages, and coastal flooding as the world warms.
We can also use various time series forecasts.

We have confirmed that global warming is a major challenge for our global society. There is little doubt that global warming will change our climate in the next century.

We have also built a model for temperature forecasting to predict the temperature for the future, and we can use that prediction for analyzing the growth in the average temperature.

So what are the solutions to global warming?

- First, there must be an international political solution.
- Second, funding for developing cheap and clean energy production must be increased, as all economic development is based on increasing energy usage.
- We must not pin all our hopes on global politics and clean energy technology, so we must prepare for the worst and adapt.

If implemented now, many of the costs and damage that could be caused by changing climate can be mitigated.