Part A

What is weather forecasting?

Weather forecasting is the prediction of the weather through techniques that can read measurements of existing weather through time and decode it in a way that it is able to give predictions on future weather. This means that the techniques can understand the flow of the weather in a given area and give predictions on what's to come [1].

What are the challenges?

One of the key challenges with weather forecasting is that we are trying to predict something that is very unpredictable. We are looking at the atmosphere when predicting, and this can be seen as a very chaotic system. If there is a slight change in the atmosphere where we are trying to predict, it can have huge consequences in flow of what's "normal" in that area. So even though we have the data needed to try to predict, there will always be assumptions in the end since it's basically impossible to try to model the atmosphere 100% without some errors [2].

Why LSTM is suitable to deal with weather forecasting.

Since weather forecasting generally uses big datasets to predict to avoid errors, the LSTM is quite suitable to the fact that the model uses a long-term memory to understand the flow of the whole dataset so it can predict what to come. So, it's very good for sequential data.

How is it better than other techniques when dealing with weather forecasting?

<u>Linear regression</u>

Linear regression is a regression model that assumes that there is a linear relationship between the target variable, and the other dependent variables. Even though it sounds good for forecasting, the model is limited. Since Time series can be unpredictable, and LSTM contains feedback mechanisms to sort that out, LSTM is superior [3].

a

<u>ARIMA Time Series Forecasting</u>

ARIMA stands for Autoregressive Integrated Moving Average and is a popular model for forecasting. This model requires that the dataset is stationary, meaning that the mean, variance, and autocorrelation do not change over time. This means that the model works best when the data used have linear patterns and does not have complex non-linear relationships. Also, its more preferred if the data is univariate (single variable). This is where LSTM excels as it does not care for relationship between the variables [4].

<u>Random forest regression</u>

Random forest regression is a method that uses different decision trees to make a prediction based on all decision trees in play. This means that it selects the best tree for prediction. Again, LSTM is superior to this technique for the fact that it can handle much more data efficient than RF due to vanishing/exploding gradient. It also needs the data to be univariate [5].

XGBoost

Extreme Gradient Boosting and is a specific implementation of gradient boosting. It uses advanced regularization which improves model generalization and reduces overfitting [6]. As the RF model, XGBoost needs to change the dataset to supervised learning [7].

Part B

What is the content of the selected articles?

The content of the selected articles mainly focuses on the implementation of the LSTM that is used to predict weather forecasting. Some of the articles uses a hybrid version of the model to gain better accuracy.

How are they relevant to your work?

They are relevant in my work since I can understand better to how I'm going to work with weather forecasting and improve my LSTM model. They show me different approaches to weather forecasting, and implementation of the model.

An LSTM Short-Term Solar Irradiance Forecasting Under Complicated Weather Conditions.

The goal of this article

The goal of this article is to predict Solar Irradiance one hour in advance and one day in advance using LSTM so that there will be safe to operate the grid and improve the economics of the PV (photovoltaic) system, which is a system designed to supply usable solar power.

The methodology used.

They implemented LSTM and used four performance metrics to evaluate the forecast model. RMSE (root means squared error), MAE (Mean absolute error), MAPE (Mean absolute percentage error) and R-Square.

RMSE measures the difference between actual values and the forecasted values. A lower value indicates better forecasting results.

MAE is the average of absolute errors. It's used to better reflect the accuracy of the forecasting value error.

MAPE reflects the ratio of error to true value in percentage.

R-Square judges whether the predictive model is fitting and reflects the prediction deviates from reality. A 0 means the model fits poorly, while a 1 means the model has no errors.

RMSE and MAE evaluates hourly forecast while MAPE evaluates the daily forecasts.

ARIMA, SVR, BPNN, CNN and RNN where also implemented to compare.

The weather is divided into Sunny, Cloudy, Mixed, and all.

The result the study gave.

Daily forecast

Location	Model	RMSE (W/m^2)				MAE (W/m^2)				R^2			
		Sunny	Cloudy	Mixed	All	Sunny	Cloudy	Mixed	All	Sunny	Cloudy	Mixed	All
Atlanta	ARIMA	30.44	58.06	166.88	110.78	24.26	53.56	122.639	71.48	0.97	0.86	0.57	0.86
	SVR	35.14	69.49	172.53	116.45	23.33	61.62	132.58	75.84	0.97	0.78	0.49	0.84
	BPNN	31.34	80.19	174.91	112.56	23.07	65.01	134.44	74.17	0.98	0.73	0.45	0.84
	CNN	52.55	65.32	194.64	122.36	44.00	50.50	139.47	77.99	0.96	0.72	0.32	0.82
	RNN	30.10	38.69	130.66	80.57	26.28	30.65	90.55	49.83	**0.99**	0.94	0.70	0.92
	LSTM	**28.65**	**27.18**	**68.89**	**45.84**	**22.82**	**19.11**	**53.65**	**31.86**	**0.99**	**0.97**	**0.92**	**0.97**
New York	ARIMA	42.27	42.66	96.37	65.56	34.23	30.66	74.37	46.58	0.97	0.83	0.83	0.93
	SVR	53.87	61.49	117.38	79.23	42.49	62.36	88.064	57.64	0.96	0.45	0.74	0.90
	BPNN	59.04	69.89	123.10	88.55	43.35	51.11	95.59	63.35	0.95	0.55	0.72	0.88
	CNN	56.15	83.75	124.95	92.70	38.70	63.46	89.01	63.72	0.95	0.35	0.71	0.87
	RNN	54.93	32.49	77.08	57.77	44.81	22.85	60.24	42.64	0.96	0.90	0.89	0.93
	LSTM	**32.05**	**29.59**	**56.86**	**41.37**	**22.56**	**22.03**	**45.97**	**30.19**	**0.99**	**0.92**	**0.94**	**0.97**
Hawaii	ARIMA	35.29	121.49	174.35	133.71	26.26	94.86	139.67	90.50	0.98	0.57	0.60	0.80
	SVR	48.01.	155.22	176.06	144.43	48.65	108.71	149.29	96.25	0.95	0.31	0.48	0.75
	BPNN	80.40	123.49	178.44	133.61	60.13	86.76	132.96	93.29	0.91	0.56	0.52	0.78
	CNN	42.91	159.14	195.92	147.82	35.24	109.42	146.48	97.04	0.97	0.26	0.42	0.74
	RNN	29.90	108.17	183.29	124.09	21.17	83.66	125.08	77.30	0.98	0.66	0.79	0.81
	LSTM	**22.13**	**73.07**	**86.68**	**66.69**	**18.72**	**54.34**	**65.07**	**46.04**	**0.99**	**0.91**	**0.90**	**0.95**

Location	Model	MAPE%				R^2			
		Sunny	Cloudy	Mixed	All	Sunny	Cloudy	Mixed	All
Atlanta	ARIMA	10.9	22.9	12.5	12.9	0.79	0.70	0.83	0.87
	SVR	11.6	23.8	17.3	14.8	0.77	0.70	0.72	0.83
	BPNN	16.2	42.1	19.7	21.0	0.76	0.34	0.54	0.59
	CNN	10.4	29.6	16.9	12.5	0.81	0.68	0.80	0.85
	RNN	**5.6**	19.6	7.1	9.4	0.91	0.72	0.93	0.91
	LSTM	7.3	**14.9**	**6.8**	**8.0**	**0.93**	**0.86**	**0.94**	**0.92**
New York	ARIMA	8.5	29.8	21.5	16.7	0.90	0.69	0.73	0.89
	SVR	11.5	36.7	21.6	20.9	0.89	0.67	0.77	0.85
	BPNN	22.5	61.6	22.1	25.9	0.54	0.22	0.82	0.78
	CNN	9.4	39.3	21.0	17.7	0.84	0.67	0.80	0.90
	RNN	**7.5**	27.2	25.5	14.5	**0.91**	0.74	0.78	0.91
	LSTM	9.3	**20.1**	**15.3**	**11.1**	0.90	**0.85**	**0.93**	**0.95**
Hawaii	ARIMA	14.4	38.7	15.4	12.5	0.80	0.53	0.76	0.77
	SVR	17.7	32.8	19.4	15.3	0.77	0.54	0.76	0.78
	BPNN	32.0	59.7	23.8	29.9	0.57	0.37	0.43	0.54
	CNN	12.2	32.1	7.3	11.1	0.83	0.54	0.92	0.70
	RNN	10.5	24.9	7.5	9.8	0.88	0.66	0.92	0.81
	LSTM	**5.9**	**18.1**	**6.2**	**8.2**	**0.95**	**0.86**	**0.95**	**0.91**

Monthly forecast

Location	Model	MAPE%											
		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct	Nov.	Dec.
Atlanta	ARIMA	15.6	11.3	12.4	10.4	10.5	5.8	9.2	9.8	11.7	11.0	8.9	17.6
	SVR	18.6	15.6	15.5	12.3	14.7	11.9	8.0	12.1	12.3	15.0	10.4	20.2
	BPNN	26.9	24.6	20.5	18.2	10.2	12.6	12.2	14.9	12.5	18.5	22.9	41.2
	CNN	15.4	10.9	11.2	9.8	11.6	10.1	12.7	14.6	**8.0**	11.4	9.2	21.3
	RNN	11.3	11.6	7.8	**7.9**	7.8	7.9	7.1	7.0	8.9	10.5	9.5	15.9
	LSTM	**10.6**	**10.6**	**7.8**	8.2	**7.7**	**5.1**	**6.0**	**5.9**	9.5	**10.3**	**8.2**	**13.4**
New York	ARIMA	28.2	30.7	**15.8**	13.0	13.2	12.2	11.6	11.6	12.7	22.6	33.7	28.3
	SVR	35.9	35.4	23.0	17.1	14.1	16.4	15.3	12.9	11.3	28.0	40.4	25.1
	BPNN	33.2	37.5	33.5	28.4	17.3	20.5	13.5	18.1	23.8	22.2	54.9	20.3
	CNN	27.8	24.8	18.8	13.4	10.2	15.8	12.7	12.0	11.5	21.9	22.9	25.7
	RNN	26.0	26.5	21.5	10.7	14.9	12.6	9.7	10.7	12.5	24.0	36.0	23.6
	LSTM	**20.3**	**20.3**	18.5	**9.6**	**7.8**	**7.9**	**8.1**	**7.4**	**10.4**	**19.3**	**22.7**	**19.6**
Hawaii	ARIMA	9.5	9.5	10.8	10.0	15.3	13.2	13.3	12.4	14.7	13.4	19.9	13.7
	SVR	13.2	12.6	12.8	11.5	20.9	18.8	17.5	15.4	15.6	16.4	14.1	16.6
	BPNN	21.5	19.4	35.5	35.9	31.7	40.9	30.3	36.6	30.1	22.6	22.6	32.3
	CNN	6.8	8.1	10.2	11.1	11.2	14.7	13.2	14.3	11.3	10.5	11.3	13.7
	RNN	6.7	7.9	9.8	9.5	**9.5**	9.2	9.5	12.1	10.4	10.2	11.0	11.6
	LSTM	**3.2**	**3.5**	**5.9**	**9.4**	10.4	**7.5**	**7.3**	**9.3**	**10.2**	**6.1**	**10.3**	**10.3**

<u>The advantages/disadvantages with this study</u>

This study had very good results regarding the use of LSTM, even though it struggled with cloudy weather and when the solar irradiance where low [8].

<u>Transductive LSTM for time-series prediction: An application to weather forecasting.</u>

<u>The goal of this article</u>

The goal of this article is to implement an LSTM which uses Transductive to predict weather forecasting. It is used since it then can exploit the local information in time-series prediction. This means that the samples in the test point vicinity are considered to have higher impact on fitting the model.

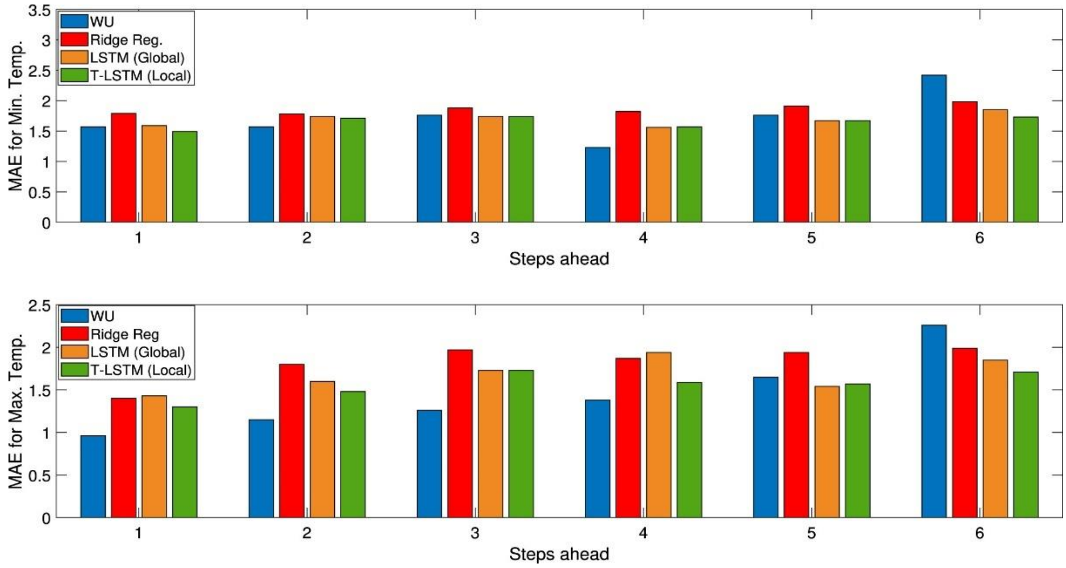
<u>The methodology used.</u>

They used a dataset from Weather Underground website that contains real measurements for cities such as Brussel, Antwerp, Liege, Amsterdam, and Eindhoven. They used TensorFlow to implement the LSTM model. They compared the Transductive LSTM with a regular LSTM to see performance. To create the T-LSTM, they altered the cost function of the LSTM such that the samples about the test point have higher impact in the objective function.

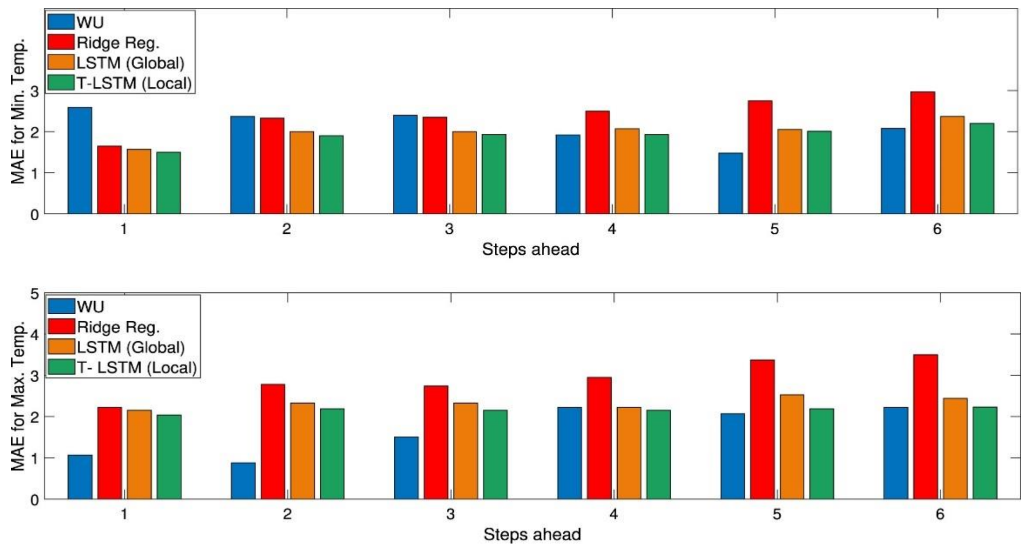
The result the study gave.

The study resulted in that the T-LSTM outperforms the LSTM in many cases.

Nov/Dec



Apr/May



The advantages/disadvantages with this study

But even though the T-LSTM had better results, the LSTM is still a very competitive approach [9].

DWFH: An improved data-driven deep weather forecasting hybrid model using Transductive Long Short-Term Memory (T-LSTM).

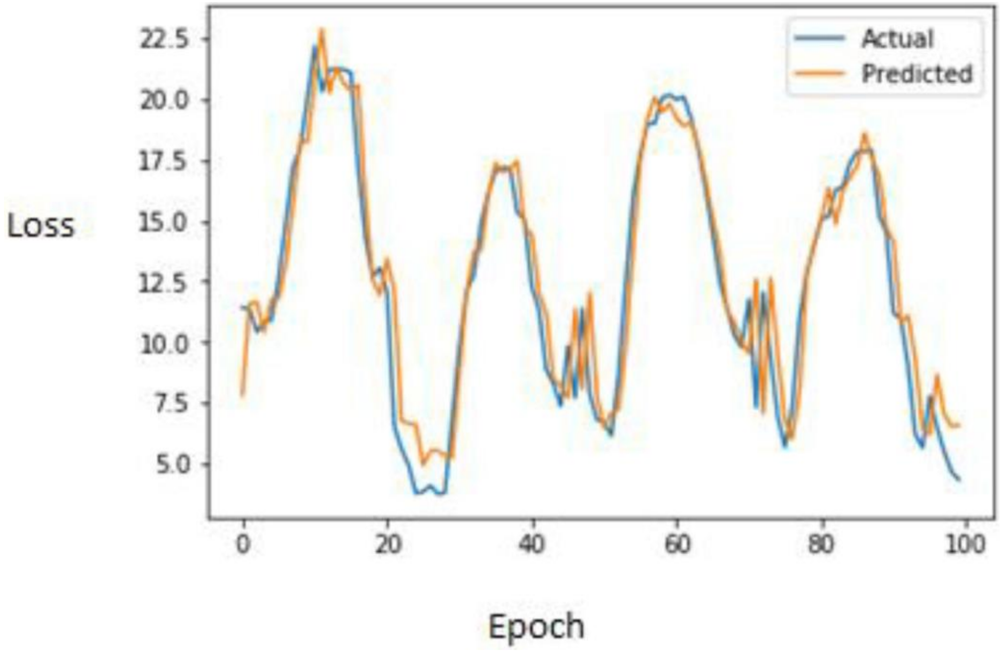
The goal of this article

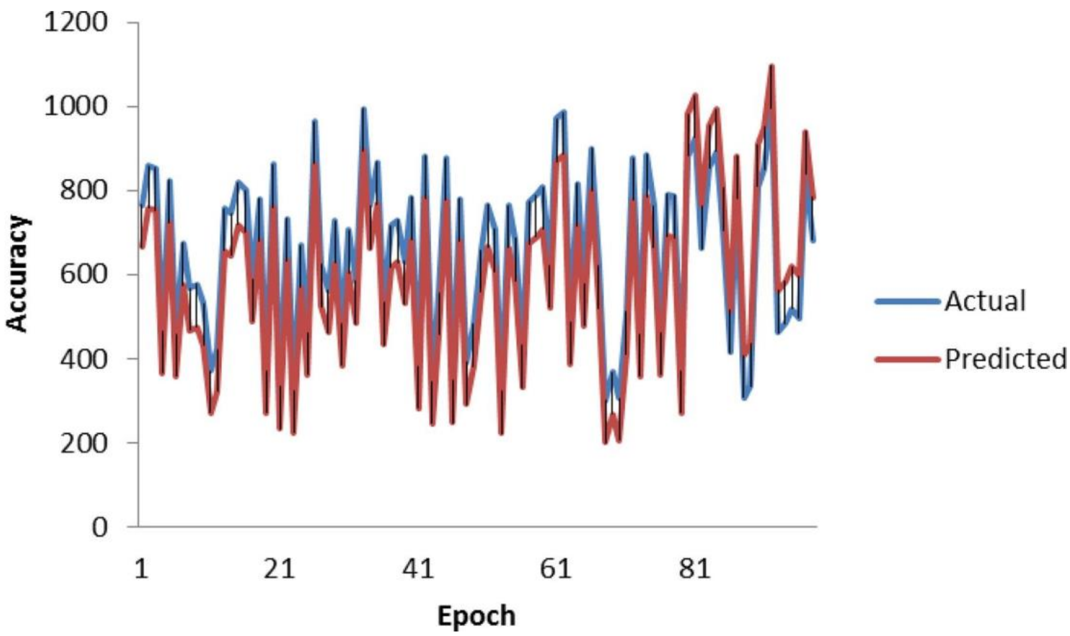
The goal of this article is to create a LSTM and T-LSTM model for weather forecasting and compare those two.

The methodology used.

They use a dataset called The Jena climate dataset that contained 14 features for the weather forecasting. They implemented the T-LSTM and LSTM with Keras and TensorFlow.

The result the study gave.





The advantages/disadvantages with this study

We can see that the hybrid approach T-LSTM is very good [10]

Application of LSTM for short term fog forecasting based on meteorological elements.

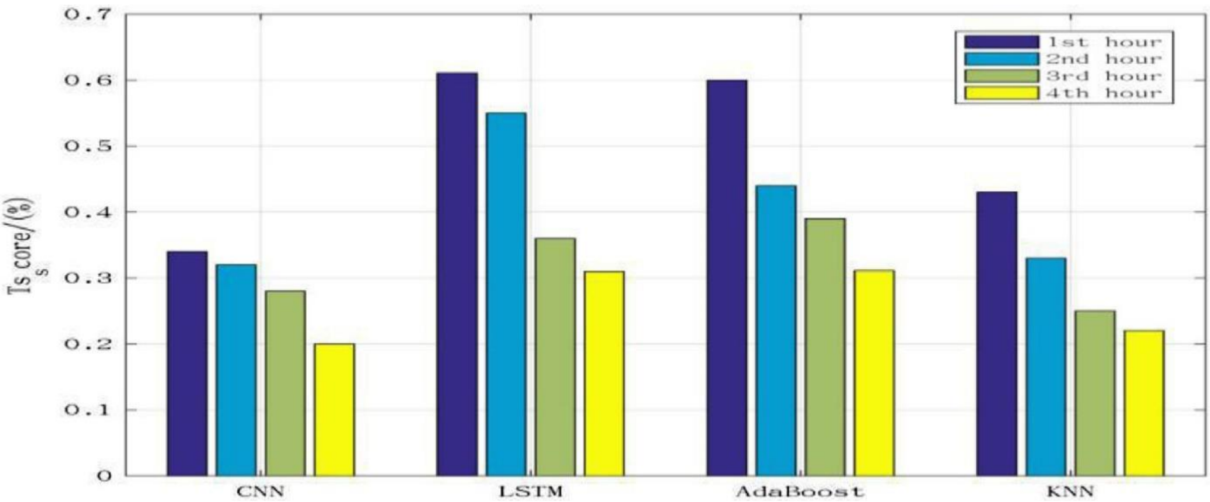
The goal of this article

Use the LSTM framework for fog forecasting.

The methodology used.

Data from Anhui Metrological Bureau of China. They have employed about 3 years of meteorological data to use on the LSTM. They also experiment with different values to find the optimal parameters for the model. They experimented with number of layers in the LSTM, number of cells in the LSTM, and the number of layers in the fully connected layer. They split the dataset into four different ones.

The result the study gave.



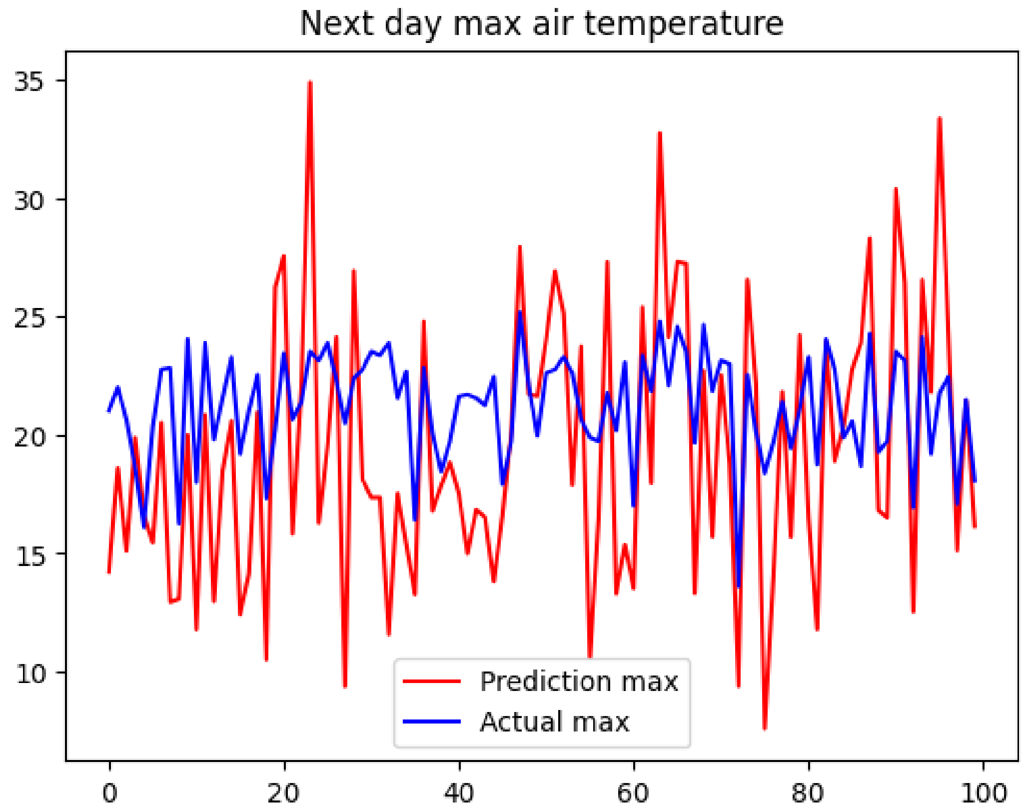
The advantages/disadvantages with this study

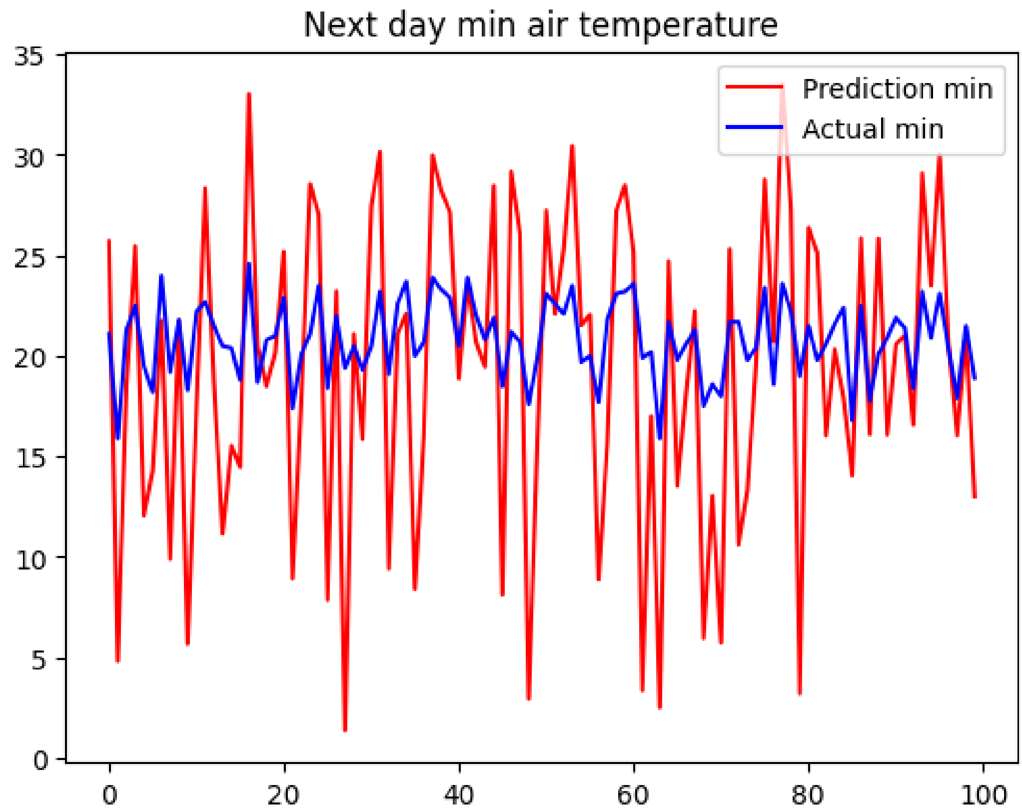
The study resulted in that the LSTM is better than the comparable models for short-term fog forecasting [11].

Part C

For my implementation, I use Keras with TensorFlow to create an LSTM model for prediction of minimum air temperature, and maximum air temperature the next day based on current value. I've used a dataset called Bias correction of numerical prediction model temperature forecast, which is a dataset that contains variables from Seoul, South Korea in the summer from 2013 to 2017. The dataset is divided into stations around Seoul, and I've decided I wanted to focus on station 1 when it comes to prediction. The variables used are Present_Tmax, Present_Tmin, lat (latitude), Ion (Longitude), DEM (Elevation), Slope, Solar radiation (Daily incoming solar radiation), Next_Tmax and Next_Tmin. I've split the dataset so that I can predict both the Next_Tmax and Next_Tmin.

Results


Next day max air temperature
Prediction max
Actual max
35
30
25
20
15
10
0
20
40
60
80
100


Next day min air temperature
Prediction min
Actual min
35
30
25
20
15
10
5
0
0
20
40
60
80
100

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