

Comparison of deep learning models for weather forecasting in different climatic zones

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ABSTRACT

Weather forecasting has become an integral part of our day-to-day life. Weather holds significant importance in our everyday lives, impacting areas such as how we travel, produce food, and maintain public well-being. Mostly, weather prediction is done with machine learning models, but the use of deep learning techniques in this field is growing. Still, the existing studies are not sufficient to get a clear concept of weather prediction in different climatic zones. Therefore, in this study, selected four deep learning models, RNN, CNN and LSTM, to predict temperature in four climatic zones. We selected four cities, Dhaka, Moscow, Dubai and Brasilia from four different climatic zones. It is seen that the overall accuracy (OA) of LSTM ranged between 85% to 95%, followed by CNN 78% to 91%, and RNN 64% to 94%. Though the OA values of these three models in four climatic zones differs significantly, high AUC values were seen in all scenario. The highest AUC value (0.999) was seen in continental climatic zone for LSTM model and lowest (0.963) in mil climatic zone for RNN.

1. Introduction

Forecasting the weather used to be a very simple task, but computers have made it much easier. Weather prediction is always helpful. Users have the opportunity to obtain weather predictions multiple times daily through mobile phone apps, TV broadcasts, newspapers, tweets, and various other sources. Climate change has long been a prevalent topic impacting people's daily lives and activities. The evaluation of climate data may raise questions about whether it should be treated as a discrete or continuous variable. It's important to people's daily lives because it affects things like transportation, farming, and public safety. The area of weather prediction has advanced significantly in recent years. This is because there is more meteorological data available, models and algorithms are getting more complicated, and machine learning techniques are being used.

The goal of this research paper is to look at the current state of the art in predicting the weather and to find the most important challenges and opportunities for future research. Climate change has caused a notable increase in both the number and severity of natural calamities, leading to the unfortunate loss of numerous lives [1]. Several experiments have been done using different models of machine learning to sort weather data. Some of the approaches that have proved to be successful are Random Forest [2], SVM [3] [4], Multinomial Naive Bayes [4], Linear Regression [5], etc. Also, for weather forecasting, several boosting algorithms were also used such as Gradient Boosting [6], Ada Boosting [7], XG Boosting [8], etc.

SVM can be used for both numerical data and textual data [3], [4]. In paper [3], the weather kinds are determined using data analysis as opposed to meteorological instruments. Using a direct SVM for training multiclass predictors, a model of weather prediction is developed. Although SVM is ideal for classification, the outcomes of classification rely on the kernel type, kernel parameters, and soft margin coefficient, which are difficult to choose. In this study, the particle swarm optimization (PSO)

technique was used to improve these parameters such that accurate predictions may be made. The predictions indicate that this strategy was practicable and successful. Also, in paper [4], SVM was also used for text classification and performed very well. This paper's aim was to classify the weather based on Twitter.

In this study [5], the author provided a benchmark data set for data-driven medium-range weather forecasting (3–5 days), a subject of great scientific interest to both atmospheric and computer scientists. They offered processed data extracted from the ERA5 archive that may be used in machine learning algorithms. The author presented straightforward and easy assessment measures that would facilitate direct comparisons between various methodologies. In addition, they offered scores from basic linear regression approaches, deep learning models, and simply physical forecasting models as baselines.

Artificial Neural Network, Gradient Boosting XG Boosting, etc. algorithms were also used for weather prediction in [6], [7], [8]. In [6] paper, In order to construct weather prediction models, Artificial Neural Networks and Gradient Boosting classifiers were developed, and comparisons between these two models are also done for this dataset. Parameters such as average temperature, average dew point, average sea level pressure, the average percentage of humidity, etc. are taken into account to determine the local climate. Using these parameters, the trained models classified the weather as rainy (thunderstorm or not), non-rainy, snowy, or foggy. In this paper [6], the authors worked on AdaBoosting, XGboosting, Stacking KNN, and Stacking Neural Network, among others, to confirm their performance and distinguish their scores on Confusion matrix measures. They differentiated the performance of various algorithms, particularly Stacking Neural Network, due to their remarkable accomplishments.

This research [9] presented a unique use of machine learning approaches to comprehend, anticipate, and minimize the uncertainty in WRF model precipitation predictions resulting from the interplay of numerous physical processes included in the model. The numerical model used in Japan is made up of three models: a mesoscale model with a horizontal resolution of 10 km that covers East Asia, a regional model with a horizontal resolution of 20 km, and a global model with a horizontal resolution of 50 km. The short-term forecast is based on a single calculation with the best starting point. The 1-month forecast, on the other hand, is based on statistics from 26 simulations with slightly different starting points (ensemble forecast) [10].

Two hybrid NWP and ANN models for wind power forecasting across a very complicated terrain are presented in this article [11]. The created models have a high temporal resolution and a big prediction horizon (>6 h ahead). Model 1 estimates each wind turbine's energy output directly. Model 2 anticipates wind speed before converting it to power using a fitted power curve. On the performance of the model, numerous modeling choices (selection of inputs, network architectures, etc.) are studied. The performance of various models is assessed using four normalized error metrics. The statistical outcomes of model predictions are provided with accompanying explanations. Python was used to automate tasks and for machine learning. The final product is a fully functional library for wind power forecasts and a set of tools for running the models in forecast mode. It is shown that the suggested models are capable of producing accurate wind farm power projections for sites with complicated topography and flow. The normalized Mean Absolute Error and Root Mean Squared Error for Model 2 are 8.76% and 13.03%, respectively, which are less than the errors reported by other models in the same category.

Data mining methods also can be used for weather prediction. Algorithms, such as Back Propagation, Nave Bayesian, and Decision Tree Induction, are used to forecast the weather based on a variety of characteristics. The authors of this [12] study proposed a Cumulative Distribution Function (CDF) for modeling and analysis of complicated data for weather forecasting. This technique worked well and provided more precision in predicting climate change in the near future.

In this research [13], the authors used LSTM to develop a data-driven forecasting model for a weather forecasting application. In addition, they introduced Transductive LSTM (T-LSTM), which uses local information for time-series prediction. In transductive learning, samples around the test point were deemed to have a greater influence on model fit. A quadratic cost function was examined for the regression issue in this research. The goal function was localized by evaluating a weighted quadratic cost function in which the samples around the test point had greater weights. The author examined two weighting techniques based on the cosine similarity between training samples and the test point. Experiments are undertaken over two distinct time periods of the year in order to evaluate the effectiveness of the suggested approach in various weather circumstances. The results demonstrated that T-LSTM achieves superior performance on the prediction challenge. Algorithms like ARIMA, SARIMA etc can also be used for weather predictions. This study [14] examined time series and seasonal analysis of the monthly mean minimum and maximum temperatures and precipitation for the Bhagirathi river basin in Uttarakhand, India. The seasonal ARIMA (SARIMA) model was used to provide 20-year forecasts (2001–2020). The auto-regressive (p) integrated (d) moving average (q) (ARIMA) model is based on the Box Jenkins technique, which anticipates future trends by stabilizing the data and reducing seasonality. It was determined that SARIMA(0,1,1)(0,1,1)₁₂ (with constant) was the best model for time series analysis of precipitation data, whereas SARIMA(0,1,0)(0,1,1)₁₂ was the best model for time series analysis of temperature data (with constant). The findings of the model's prediction indicate that the projected data corresponds well with the data's trend.

This paper aims to research four different locations' weather data and analyze the results. Three Deep Learning algorithms are used to analyze the data. The algorithms are CNN, RNN, and LSTM. The four different locations are Bangladesh, Russia, Dubai, and Brazil. These four locations were chosen because of their different weather conditions. These three algorithms will be implemented on one location's weather data. After that, the highest-performed algorithm will be implemented in the other three locations' weather data to see if the algorithm can perform the same or different on different locations' data.

2. Methods

2.1 Data collection and preprocessing

The research methodology involved gathering daily weather data for Dhaka, Moscow, Dubai, and Brasilia from NASA POWER [14] meteorological data. This dataset covered the period from January 1, 2000, to December 31, 2020, resulting in a total of 29,200 data points. The selection of these cities was based on their climatic zones, aiming to capture the diverse weather patterns characteristic of different regions. Dhaka represents the tropical climatic zone, Moscow the continental climatic zone, Dubai the dry climatic zone, and Brasilia the mid climatic zone. This geographical diversity enriches the dataset and enhances the comprehensiveness and reliability of the weather forecasting model.

Each dataset comprised 16 attributes containing weather information specific to the selected regions. Among these attributes, temperature (T2M) was chosen as the target variable for prediction, while the remaining 15 attributes served as independent variables. Correlation graphs depicting the relationships between these variables are presented in Figure 1. Prior to prediction, the temperature range was divided into 10 classes for each city to facilitate analysis and interpretation. For further details regarding the weather data used in the study, please refer to Table 1.

Table 1. Attribute used in this study

Attribute Name	Data Type	Description
T2M	Double	In the time of interest, the minimum hourly air temperature at 2 meters above the earth's surface. This feature was divided into ten categories.
T2MWET	Double	The adiabatic saturation temperature, which may be determined at 2 meters above the earth's surface using a thermometer coated in a water-soaked fabric through which air is circulated.

Attribute Name	Data Type	Description
T2M	Double	In the time of interest, the minimum hourly air temperature at 2 meters above the earth's surface. This feature was divided into ten categories.
TS	Double	The average surface temperature of the Earth.
T2M_RANGE	Double	The minimum and highest hourly air (dry bulb) temperature range at 2 meters above the earth's surface during the study period.
T2M_MAX	Double	Maximum temperature at 2 meters above earth surface
T2M_MIN	Double	Minimum temperature at 2 meters above earth surface
PRECTOTCORR	Double	The bias-corrected average of the total amount of precipitation at the earth's surface expressed in water mass (including snow content)
RH2M	Double	The percentage ratio of the actual partial pressure of water vapor to the partial pressure at saturation.
QV2M	Double	At 2 meters, the mass of water vapor divided by the total amount of air (g water/kg total air).
T2MDEW	Double	The temperature at the dew/frost point at 2 meters above the earth's surface.
PS	Double	The average surface pressure at the ground atmosphere.
WS10M	Double	The average wind speed at 10 meters above the earth's surface.
WS10M_MAX	Double	Peak wind speed 10 meters above the ground
WS10M_MIN	Double	Lowest wind speed 10 meters high from the surface
WS10M_RANGE	Double	The minimum and highest hourly wind speeds are measured at 10 meters above the earth's surface.
WD10M	Double	The average wind direction at 10 meters above the earth's surface.

3.1 Deep learning algorithms

- **RNN:** From a feed-forward neural network, RNN was created. It has a cyclic connection structure that obtains a memory function by repeating the computation from the previous loop iteration, in contrast to conventional feed-forward neural networks. Regarding the non-linear properties of sequence data, RNN offers a significant learning advantage [15]. RNN has gained notable success in handling temporal data as a deep learning algorithm [16]. RNN-based architectures have the potential to be perfect for multi-step forecasting applications using spatiotemporal data because of their capacity to predict long sequences and respect the temporal order [17].
- **LSTM:** The vanishing gradient issue that arises when an RNN learns sequences with long-term dependency is resolved by LSTM networks. LSTM is a lot more intricate than RNN, which has a straightforward structure [15].
- **CNN:** CNN is a three-layer feed-forward neural network type: a fully connected layer, a convolution layer, and a sampling layer. CNN is often used for applications including object identification, time-series prediction, and hand gesture classification. The convolution layer is the essential component of CNN. A convolution kernel's operation efficiently learns the data's intricate spatial properties and invariant structure [15]. With its various network designs, including 1D, 2D, and 3D-CNN, CNN is one of the most important and prominent deep learning algorithms [16].

3.2 Validation

We utilized overall accuracy and area under the ROC curve (AUC) scores to compare models for different climatic zones and to verify the validity of the data. An overview of the receiver operating characteristic (ROC) study is provided by the AUC. With values ranging from 0 to 1, this cutoff-independent measure denotes improved model performance. OA indicates the overall predictability of the model. This OA value is the proportion of correctly classified points and total point. The following equation used to calculate OA:

$$OA = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where, TP is the true positive value, TN is the true negative value, FP is the false positive value and FN is the false negative value.

3. Results and Discussion

The correlation heat maps for Dhaka, Moscow, Dubai and Brasilia are shown in the Figure 1.

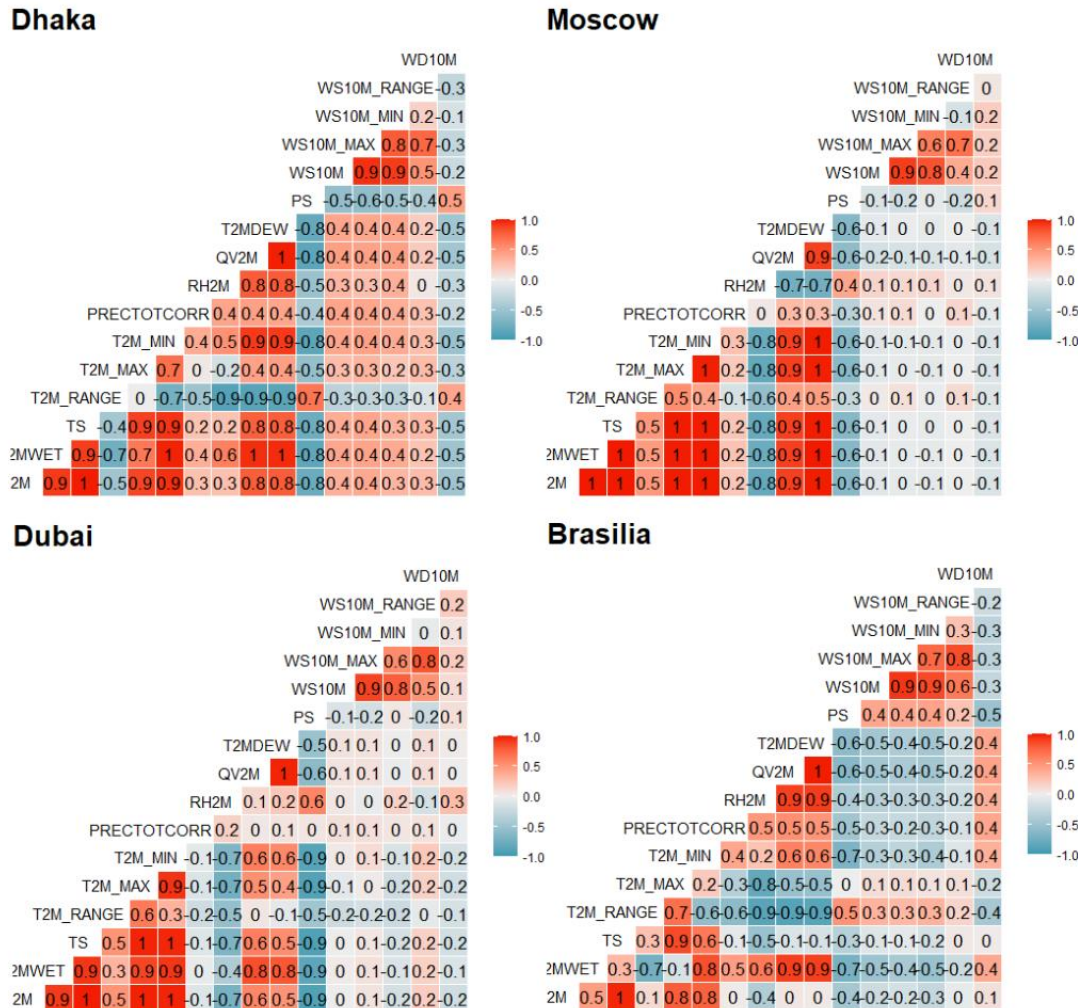


Figure 1. Correlation heat maps for Dhaka, Moscow, Dubai and Brasilia

- Model performance for Dhaka:** We applied RNN, CNN and LSTM models to predict temperature of Dhaka city. LSTM showed the highest accuracy value (92.0%) followed by CNN (83.3%) and RNN (77.7%). Among the three models, predictability of LSTM and CNN are excellent and good respectively. Thus, these two models are reliable when it comes to temperature prediction. Contrastingly, RNN showed poor performance; therefore, not reliable. The performance of the models for Dhaka city are shown in Figure 2.

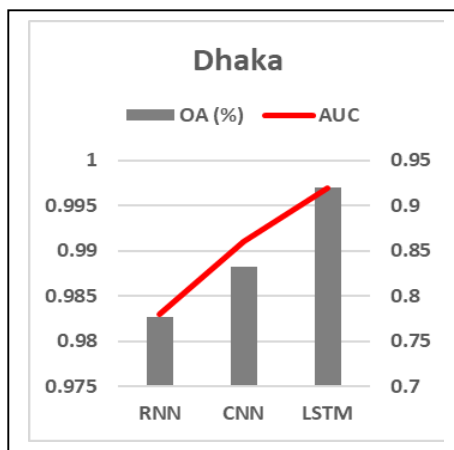


Figure 2. Performance of the models for tropical climatic zone (Dhaka)

- Model performance for Moscow, Dubai and Brasilia:** We have also used the previously used four models for Dhaka city to understand if the models are giving same kind of accuracy for other cities. Like Dhaka, LSTM performed highest for Moscow with an overall accuracy of 94.8%. Though the value is little high from Dhaka, both the accuracies are considered as excellent result. However, OA of CNN and RNN of Moscow are 90.7% and 93.3%, respectively, which differs significantly from Dhaka. Though RNN showed low performance in Dhaka, for Moscow this model exhibited excellent performance.

For Dubai, the performance of the models followed the same trend as Moscow. LSTM performed the highest with an OA of 90.5%, followed by RNN (87.4%) and CNN (82.6%). Though LSTM showed the best performance for Dubai, the OA values are relatively lower than Dhaka and Moscow. Unlike RNN result for Dhaka, the model performed good for in Dubai.

Finally for Brasilia, the performance of the models are lowest among all four cities. Where of LSTM showed excellent predictability in Dhaka, Moscow and Dubai, Brasilia showed an OA of 85.1%, which is considered as a good result. Accuracy of CNN and RNN was 78.6% and 64.1%. Both the results are poor and not reliable.

Overall, it is seen that LSTM performed best for all the four cities but the accuracy values were different for all. RNN was the second-best performer for Moscow and Dubai, but for Dhaka and Brasilia it was the least performed model. On the other hand, CNN values were good for Dhaka Dubai and Moscow, but poor for Brasilia.

From the result, it can be concluded that, in all of the climatic regions, tropical (Dhaka), dry (Dubai), mild (Brasilia) and continental (Moscow), LSTM is the best model that for temperature prediction. But the level of accuracy is not uniform for all regions. Except in mild climatic zone, LSTM excellently performed in other climatic regions. On the other hand, CNN is not a great fit for temperature prediction in mild and dry climatic regions. Along with CNN, RNN poorly performed mild climatic region. The same scenario is seen with RNN in tropical climatic region. The performance of the models for Moscow, Dubai and Brasilia is shown in Figure 3.

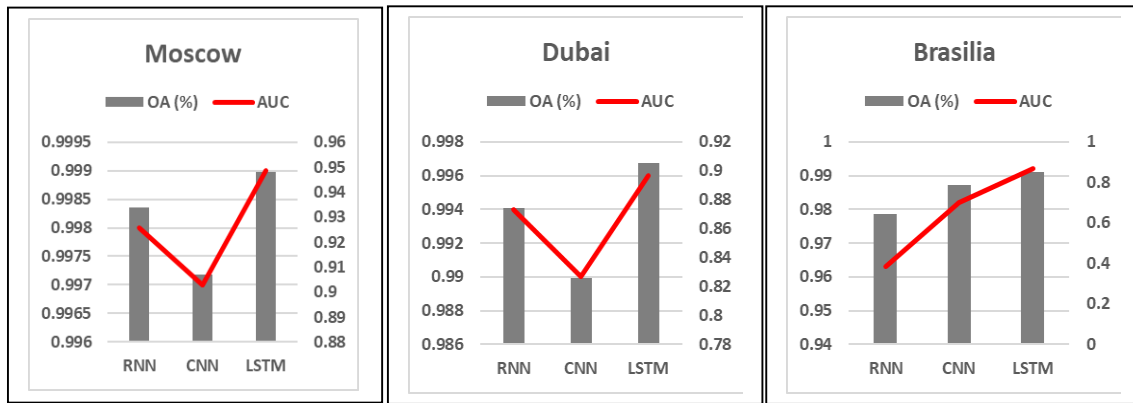


Figure 3. Performance of the models for dry (Dubai), mild (Brasilia) and continental (Moscow) climatic zone (Dhaka)

High AUC values are consistently obtained in all circumstances, highlighting the model's capacity to differentiate well. The LSTM model, in particular, comes out with the greatest AUC of 0.999, particularly in the continental climate zone. This excellent AUC value validates the LSTM model's superior forecasting performance in capturing complex patterns in these climate zones. The RNN model, on the other hand, reported the lowest AUC value of 0.963 in the military climate zone, although displaying differences in AUC values between climatic zones. This observation encouraged more research into the intricacies of model performance in various situations. Overall, including AUC considerations in our study attempts to emphasize models' abilities to produce complex predictions and distinguish between different climate circumstances.

4. Conclusion

In this study, we selected three popularly used deep learning models, RNN, CNN and LSTM, to investigate if the performance of these models are similar in all climatic zones. For this, we selected for cities (Dhaka, Moscow, Dubai and Brasilia) from four different climatic zones (tropical, continental, dry and mid). We found that the performance of these models is not uniform in all climatic zones. Though LSTM, showed the highest predictability in all for climatic regions, but the accuracy level is different. Except in mild climatic zone the performance of CNN was reliable for other three climatic zones. However, RNN showed reliable accuracy for continental and dry climatic zones.

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