Refinement Model Based on Deep Learning Technique for Prediction of Temperature Using Missing Data

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Abstract

Researchers have recently turned their focus to time sequence predicting of meteorological such as daily heat in an effort to overcome the limitations of standard forecasting methods. Due to the difficulty of the task, it is difficult to create and choice an precise time-series forecast perfect. This is a critical factor in human life and many other areas, including agriculture and manufacturing. People's health will be adversely affected by an increase in temperatures in the highland urban heat, especially in the summer, as a result of this. As a result of this paper's research, a novel temperature prediction model based on deep learning has been developed (i.e., the progressive deep cascade categorization model). In order to achieve this, a large volume of high-quality model training data is required. A drawback to weather data collection is the inability to measure data that has been overlooked. There is a high probability of missing or incorrect data due to the nature of data collection. To make up for the lost weather data, the proposed temperature prediction ideal is being used to fine-tune the existing data. Research also uses a deep learning network for time-series data modelling because the temperature changes throughout the year. Various deep learning techniques are also being examined to verify the model's efficacy. In particular, the suggested model's refinement function can be used to restore lost data. The model is retrained using the refined data after all the missing data is refined. Finally, the proposed model for predicting temperature has the capability of doing so. The suggested model's (RMSE) root-mean-squared error, accuracy, precision, and recall are used to evaluate its performance.

Keywords: Weather Data; Temperature Prediction; Time-Series Prediction; Missing Data; Progressive Deep Cascade Classification; Refining Data.

Introduction

Humans have undergone a variety of weather and climate variations since the beginning of human history, some of which have prompted people to relocate. Dangerous weather phenomena, such as heat waves and torrential deluges, are becoming extra shared and penetrating as a result of climate alteration. Both the environment and human activities are harmed by these changes [1], which are potentially life-threatening. The rate of weather change has accelerated in the last decade, and numerous research have been done to determine the causes of the shift and devise solutions [2]. For example, air quality, wind speed, and electricity consumption can all be predicted using deep learning techniques that have recently gained popularity [3–5].

Throughout the previous few decades, there has been an upsurge in the frequency of thrilling weather events such cold weather, heavy snowfall, torrential rain, and drought, all of which cause harm to people's health and property [6]. People's lives are negatively affected by weather change, in other words. [7] Outdoor workers are particularly vulnerable to unexpectedly high temperatures. Using temperature forecasts, you can decide what to dress and where to work on any given day[8]. At least 10 days' forecast should be provided for each site or region where the temperature forecast is to be used [9].

Numerical weather prediction models (NWP) are commonly used by meteorological institutes to estimate future weather conditions [10]. Over the most part, NWP models are designed to forecast weather for vast geographic areas, such as they are adept at managing weather that is intricately linked to multiple elements that have an impact on the weather the next day. According to [11], the NWP has a tendency to cause temperature anomalies as the elevation and topographical complexity of the area increases. Furthermore, NWP models have difficulty predicting temperature changes in places with complicated topography [12].

A temperature forecast model based on DL is the goal of this project, which uses real-time meteorological data. When it comes to constructing a neural network, a cascade network is used in this approach. Weather data is better suited to a proposed architecture because of its time-series features [13]. When training deep learning models, a lot of training data is required, but it must be free of any errors. The collection of meteorological data, however, has a constraint in that we can't measure data that we have missed. There is a high probability of missing or incorrect data due to the nature of data collection. The projected temperature prediction model therefore adds a missing data function into the PDC framework in order to replace lost meteorological data. The four phases of the suggested model are as follows. The model's initial step is to determine if any input data is missing. Using all of the training data, a PDC-based refinement model is built in the second stage of model training. In the third phase of the projected model, the temperature of the missing vector mechanisms is attempted to be estimated. The final phase is to use the improved data to retrain the temperature prediction model.

According to this structure, the rest of the paper is: Section 2 focuses on existing methods, whereas Section 3 explains the proposed paradigm with PDC description. Section 4 depicts the experimental analysis used to test the proposed model's classification accuracy. Section 5 concludes the investigation with a summary of the findings.

2. Literature Review

When it comes to climate data, Curceac et al. (2019) [14] use both a kernel-based regression model and a SARIMA model. There is an overview of several models, from neural networks to SVM to Markov chains that they provide in a quick but comprehensive literature review. Graf et al. (2019) [15] anticipate river temperature using wavelets and artificial neural networks. Using an ensemble of 12 independent forecasting models, Hassani et al. (2018) [16] emphasis on weather irregularities.

Aladin-HIRLAM was used to estimate air temperatures. Predicting temperature variations in complicated terrain over time and space remains a difficulty for NWP models. According to Frnda et al. [18], the European Centre for Medium-Range Weather Forecasts (ECMWF) could benefit from a neural network-based model to increase its output accuracy and highlight the potential of neural network for weather forecast development. As a result of this, artificial neural networks (ANNs) have become increasingly popular in recent years as a means of forecasting the weather. It was discovered by Fahimi et al. [19] that the most accurate model with the least error and the greatest correlation coefficient used five different neural network models to estimate Tehran's winter maximum temperature. They used this model with three variables: mean temperature, sunshine hours, and difference among extreme temperature and least temperature.

3. Proposed Methodology

With regards to training data collection, as stated in Section 1 (Introduction), the process is very challenging. In other words, the data gathered are likely to be partial, with random or long gaps. The purpose of this section is to present an alternative PDC-based temperature prediction model that joins a role for missing data modification to help fill in the data gaps.

3.1. Investigation of Weather Factors Connected to Temperature

The effects of the weather on temperature are examined in detail in this section. Data from the South Korean Meteorological Office (KMA) is used for this purpose. There are 36 years worth of hourly temperature, wind speed and direction measurements as well as relative humidity and total precipitation accumulation as well as atmospheric pressure and barometric pressure. After that, the correlation coefficients for all 36 years of temperature and other weather variables are calculated (Table 1). Wind speed, direction, and humidity are all closely related to temperature, as you can see in the chart. As a result, this paper's temperature predictions rely on variables including wind speed, direction, and humidity.

Table 1. Coefficients among temperature and other weather issues.

Weather Factors	**Wind Direction**	**Humidity Relative**	**Wind Speed**	**Vapor Pressure**	**Cumulative Precipitation**	**Barometric Pressure**
Correlation	0.71	0.64	0.69	0.25	0.38	0.30

3.2. Proposed Refinement Function Using LSTM

Temperature is linked to three weather variables (wind speed, as discussed in the preceding subsection. This means that if heat data are missing at certain times but other weather elements are accessible, the missing data can be reconstructed by using the linked features. Using the PDC as a correlator between other meteorological parameters and temperature, a refinement function of the projected model is realised.

In the suggested model, there are four phases of processing. During the first stage, the algorithm checks to see if any of the input vectors are missing, which are 4-D weather data. Each missing component is linearly interpolated using observed data from the past and future if any are lost. All training data is subjected to this procedure. Figure 1 shows the flow of the research work.

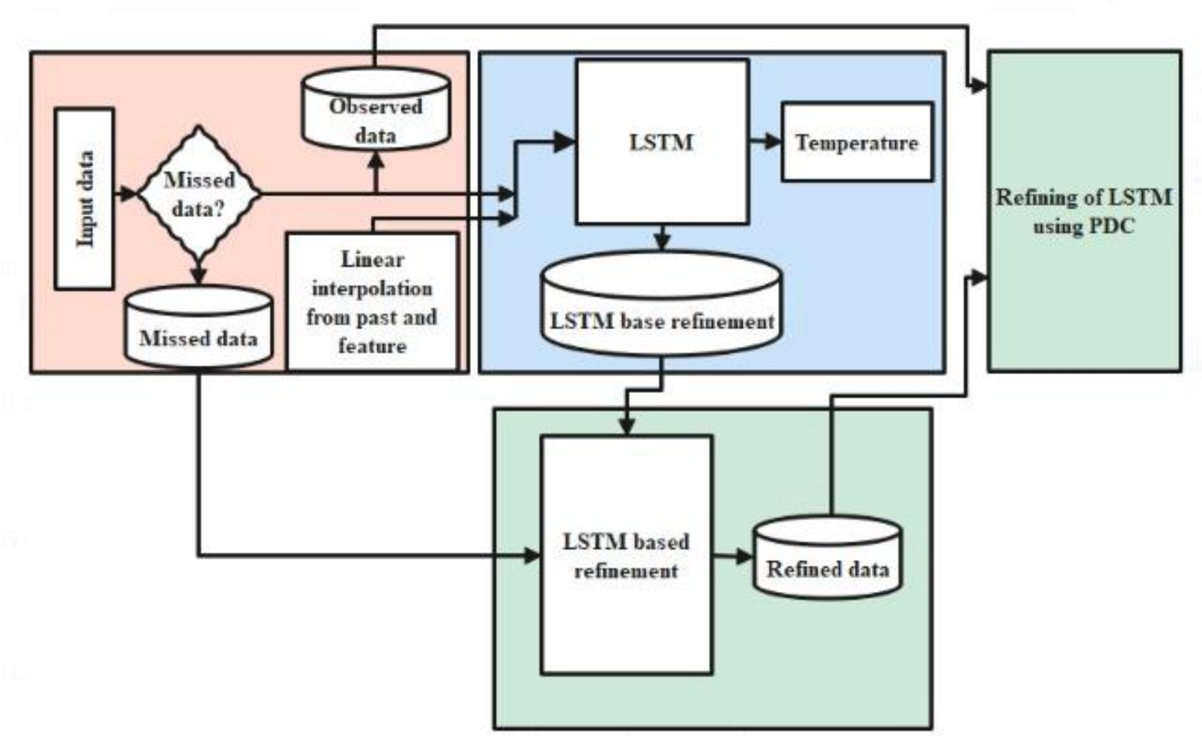

Figure 1: Working flow of the Research Model

Using all of the training data, the second stage creates a PDC refinement model that includes linear interpolation for any missing data. The following is a definition of the PDC-based refining model:

It is usual for researchers to increase the number of traits when they have no prior knowledge. This can lead to feature redundancy as well as an increase in computation complexity and a corresponding increase in computer resources. Consequently, we propose a progressive deep cascade classification model (PDC).

3.2.1. Progressive cascade classification

The class likelihood of a sample is used to classify PDC. Random forest is an collective learning process that employs averaging to increase predictive accuracy and control overfitting to fit a number of decision tree classifiers on numerous sub-samples of the dataset. A dataset with a large number of variables can be effectively processed using random forests. During the forest-building process, they generate an internal, unbiased guess of the generalisation error. Their ability to estimate missing data is also impressive. As a result, we begin our categorization process with RF (Random Forest). The RF identification results may be influenced by the number of attribute values due to the random nature of the forest construction process. As a result, different RFs are used to categorise the same wavelet energy vector Fl in order to overcome the characteristics' bias. The classification outcomes in each tier of the cascade are then generated by the mean class probability distribution of these RFs. When the classification accuracy of PDC does not improve any more, the cascade classification process comes to an end. It is possible to automatically identify the number of cascade layers by comparing the accuracy of the categorization. By using a progressive cascade classification, an individual sample can be identified.

Suppose there are *N* data samples $\boldsymbol{S_i} \in R^{V\times L}(i = 1,2,\dots,N)$ confidential into K classes by PDC. The feature vector of $\boldsymbol{S}_i$ in the *j*th scale is $\boldsymbol{F}_{il} = [\boldsymbol{E^i_{j1}},\dots,\boldsymbol{E^i_{jv}},\dots,\boldsymbol{E^i_{jv}}]$ $(l = J - j + 1)$. Each layer includes a set of *M* random forests, i. e.

$$RF^l_S = \{RF^l_1, RF^l_m, \dots RF^l_m\} \quad (1)$$

where $m = 1,2,\dots,M$. Each RF^i_mm l yields a classification probability vector p^l_m of S_i according to F_ij, and $p^l_m = [p^l_{m1}, p^l_{mk} \dots, p^l_{mk}](k = 1,2,\dots K; l = 1,2,\dots,L)$. p^l_{mk}represents Si has a kth-class probability based on the categorization of RF m m in the lth layer. It is thus possible to express the probability vector (Pa) of Si in the lth layer produced by M random forests as

$$\widetilde{P}^l_i = [p^1_1, \dots . p^l_m, \dots p^l_m] \quad (2)$$

Superimposing results from numerous layers can replicate the progressive recognition procedure of humans if each cascade layer's categorization result is treated as one credit of S i. Because of this, the probability distribution (P) _il of M random forests in the higher level is cascaded with those in all lower layers in the lth layer.

$$p^1_1 = [\tilde{\widetilde{P}}^l_i, \tilde{\widetilde{P}}^{l-1}_i, \dots, \widetilde{P}^1_i] \quad (3)$$

Then the *l* layers can be printed as

$\bar{p}^l_1 = [\bar{p}^l_{i1}, \bar{p}^l_{ik}, \dots \bar{p}^l_{ik}]$, where

$$\bar{p}^l_{ik} = \frac{1}{lM}\sum_{t=1}^{l}\sum_{m=1}^{M} p'_{mk} \quad (4)$$

Sample S i's class label is established by taking the class probability p _ikl with the highest value. Classification result fusion of many layers thus realises human coarse-to-fine recognition. The classification accuracy of the present model, M l, can be determined by comparing the prediction outcomes of all samples. For example, let's say A l is the prediction accuracy of model M L in the lth cascade layer. A l and A (l-1) will be compared in every layer to see if the lth should be included to the model. As a result, the PDC features a feedback cascade design. A l is a function of the number of cascade layers, so.

$$H(A_l) = \begin{cases} l & \Delta A_l < 0 \| |\Delta A_l = \Delta A_{l-1}| \| A_l = 1 \\ l+1 & others \end{cases} \quad (5)$$

where $\Delta A_l = \Delta A_{l+1} - A_l$. Eq. (5) indicates that in the following three scenarios, the categorization cascade comes to an end:

- ❖ Next layer categorization accuracy is lower than the last layer's;
- ❖ There is no increase in categorization error between successive levels;
- ❖ All samples have been accurately categorised.

According to the preceding explanation, the procedure of PDC can be summarised as follows:

$Step\ 1. Initialization$

$1\ Input\ N_1\ training\ samples\ \boldsymbol{S}_i(i = 1,2,\ldots,N)\ from\ all\ sample\ dataset. Divide\ N_1\ into\ sub-training\ set\ N_{11}\ and\ sub-test\ set\ N_{12}.$

$2\ Set\ initial\ values\ of\ M.$

$.Classification$

$1)\ For\ every\ sample\ i = 1{:}\ N_{11}$

$Input\ F_i^l\ in\ the\ sub-training\ set\ to\ the\ set\ of\ M\ random\ forests\ RF_s^l\ in\ the\ lth\ layer;$

$Generates\ the\ lth\ cascade\ probability\ distribution\ \tilde{P}_i^l by\ RF_s^l.$

$Construct\ the\ cascade\ probability\ distribution\ in\ the\ lth\ layer\ P_i^l\ and\ compute\ the\ m$

$Decide\ the\ class\ label\ of\ sample\ according\ to\ the\ largest\ class\ probability\ of\ \bar{P}_i^l.$

$End.$

$2)\ Output\ the\ temporary\ recognition\ model\ M_l.$

$2. Prediction$

$i. Input\ N_{12}\ samples\ into\ M_l.$

$ii. Predict\ the\ class\ labels\ of\ N_{12}\ samples\ according\ to\ M_l. and\ compute\ \ classificatio$

$3. Cascade$

$If\ \Delta\boldsymbol{A}_l < 0\ \|\Delta\boldsymbol{A}_l = \Delta\boldsymbol{A}_{l-1} = 0\|\boldsymbol{A}_l = 1, then\ L = l, cascade\ is\ stopped\ and\ classification\ model\ MLis\ accomplished, go\ to\ Step\ 4;\ el$

$= l + 1, go\ to\ Step\ 3-1;$

$end.$

$4. Input\ N_2\ test\ samples\ into\ M_L\ and\ output\ the\ classification\ result\ of\ \boldsymbol{S}_i(i = 1,2,\ldots,N_2).$

$End.$

It is in this third stage of the proposed PDC-based refining model that the temperature data that were already discovered are used to estimate temperatures for times when the data are unavailable. Refinement functions are used to replace the missing temperature data with the expected data. Using the refinement function, the missing data from the proposed model is refined and then mixed with the acquired data that has all of the necessary components to train the PDC.

4. Results and Discussion

4.1. UM Model

Since 2010, the KMA has used the unified model (UM) created by the UK Met Office to forecast the weather. Weather forecasting at KMA is comprised of a trifecta of NWP systems: GDAPS, RDAPS, and the Local Data Assimilation and Prediction System (LDAPS). The RDAPS and LDAPS activities, whose domains are depicted in Figure 2, are bound by the predictions of GDAPS and RDAPS.

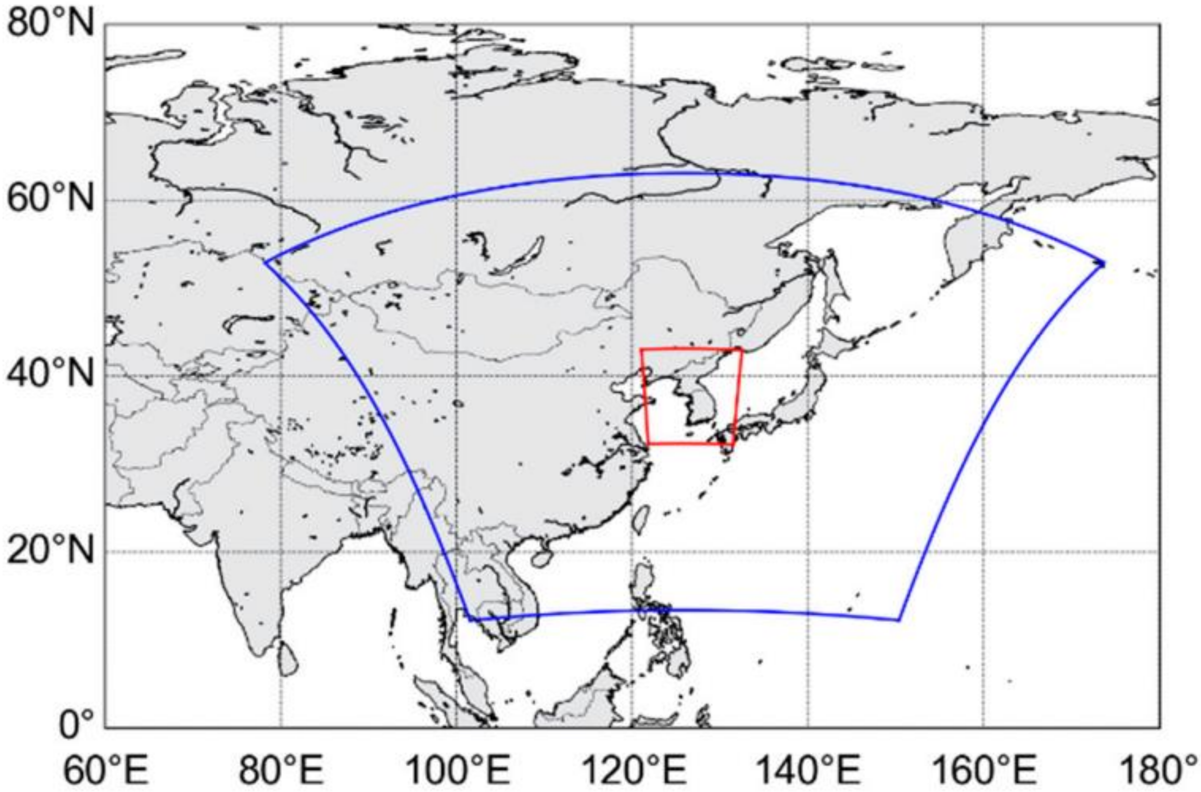

Figure 2. UM system domain, where blue and red lines signify RDAPS and LDAPS (Local Data Assimilation and Prediction System and Regional Data Integration and Prediction System, respectively). [20].

RDPAS and LDAPS, as depicted in the figure, have horizontal resolves of 12 km 12 km and 1.5 km 1.5 km, correspondingly, and cover East Asia and South Korea. The top elevations of the RDAPS and LDAPS are set to 80 and 40 km, respectively, for both systems' 70 sigma vertical layers.

For the KMA UM-based NWP system, Table 2 provides a summary of the physical alternatives that can be used. This model's anticipated temperature was tested against data from the official data archive of the University of Michigan (UM).

Table 2. Physical options of unified model based arithmetical weather prediction (NWP) scheme used in KMA.

Scheme	**Physical Options**
Mixed-phase precipitation [22]	Microphysics
Mass flux convection with convective available potential energy (CAPE) closure [23]	Cumulus scheme
Met office surface exchange scheme (MOSES)-II land-surface [24]	Land surface model scheme
First-order non-local boundary layer scheme [25]	Planetary boundary layer (PBL) scheme

Edwards-Slingo general 2-stream scheme [26]	Radiation scheme

4.2. Database

Using KMA meteorological data, we compiled hourly readings of temperature, relative humidity, wind speed, and direction for the purposes of this investigation [27]. Over a period of 37 years (from November 1981 to December 2017), weather data was collected across Seoul, Gyeonggi, and Jeolla in South Korea. These data were split into two sets: a training set of 36 years (from November 1981 to December 2016), and a test set of one year (from January to December 2017). The test set was used to determine the accuracy of the model. It should be noted that the training set's period of weather data collection did not coincide with the test set's. If there was no extra explanation for training and testing data, then all prediction models in this study were trained and assessed using the training data and test data, correspondingly. The accuracy of the model's predictions was also averaged across three locations, one for each prediction model.

4.3. Performances Metrics

Here, the proposed model's classification accuracy is tested with various DL classifiers, hence, the parameters are used that are discussed as follows:

A. **Accuracy:** Predicted connection records are estimated by dividing the whole test dataset by the number of predicted records. For DL, the better the model if it has a higher level of precision. Using an experimental dataset with balanced classes, accuracy is a suitable statistic.
B. **Precision:** If the attachment logs are successfully identified, then the estimated ratio of correctly identified attachment logs to total attachment logs is 1. If the precision is higher, the DL model is better than the ML model (Precision [0,1]). Accuracy is listed below.
C. **F1-Score:** F1-Score is also referred to as F1. The harmonic mean is precisely defined and easily recalled.

The results of the three prediction models were summed up to get an average. temperature were all absent from the training set, with 38 percent of the data missing. For the RMSE and MBE, the temperature difference between the actual and anticipated readings was divided by the time interval (t) to find the difference in temperature between Ytr and Ytp.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(\Upsilon_t^r - \Upsilon_t^p)^2}{N}} \quad (6)$$

and

$$MBE = \frac{1}{N}\sum_{t=1}^{N}(\Upsilon_t^r - \Upsilon_t^\rho) \quad (7)$$

where N is the total sum of times for the assessment.

4.4. Performance Evaluation of Proposed Model

Here, two different types of validation is carried out, i.e. 60%-40% and 80%-20% of data are used.

Table.3. *Comparative analysis of 60% 40% on Proposed with various existing algorithms.*

Algorithm	Accuracy	Precision	Recall	F-score
Linear Regression	80.10	87.21	80.15	80.43
Naive Bayes	85.71	84.32	85.93	83.45
KNN	92.10	92.43	92.15	91.68
DT	92.46	93.48	92.44	91.81
SVM	89.52	90.21	89.54	89.03
RNN	94.53	96.61	92.52	92.24
LSTM	94.16	96.17	92.32	92.10
PDC	**95.62**	**98.32**	**94.62**	**94.53**

Initially, the above Table 3 and Figure 3 shows the comparative analysis of various models for 60%-40% of weather data. In first of Linear Regression algorithm gets an accuracy value of 80.10%. In another LSTM model reaches the accuracy level of 94.16% and finally the proposed model reaches the accuracy of 95.62%, in LSTM model is nearest accuracy percentage of the proposed model.

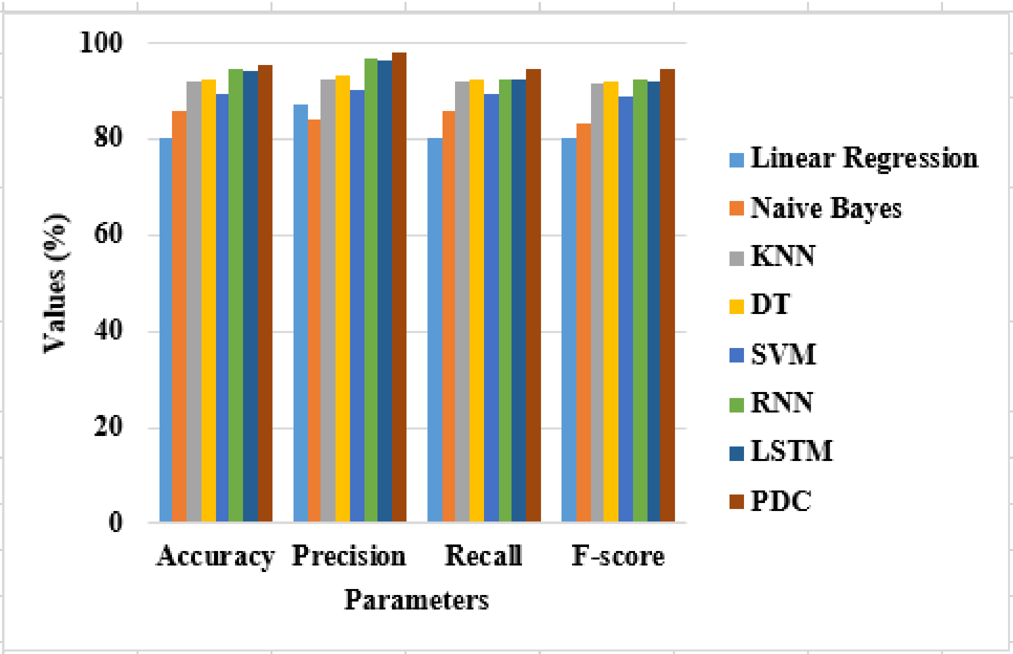

Figure 3: Comparative Analysis of proposed model in terms of various metrics for 60:40

Table.4. *Comparative analysis of 80% 20% on Proposed with various existing algorithms.*

Algorithm	Accuracy	Precision	Recall	F-score
Linear Regression	81.10	99.41	75.91	86.72
Naive Bayes	87.70	99.41	85.21	91.82
KNN	92.50	99.82	90.98	95.27
DT	92.90	99.78	91.52	95.41

SVM	92.50	99.63	91.38	95.18
RNN	92.70	99.90	91.93	95.32
LSTM	93.27	99.91	92.47	95.63
PDC	**94.32**	**99.95**	**93.24**	**96.02**

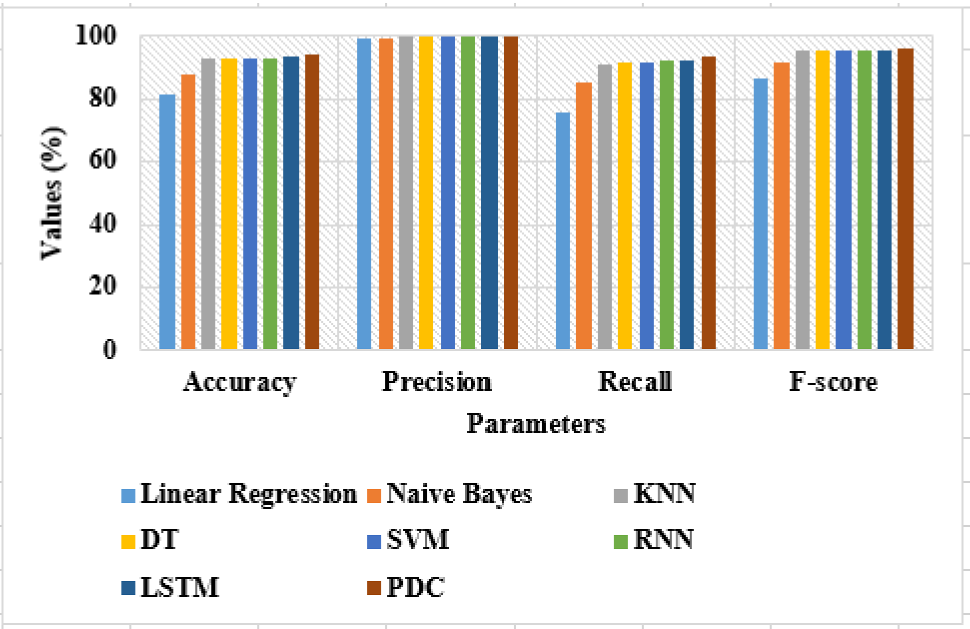

Figure 4: Comparative Analysis of proposed model in terms of various metrics for 80:20

A PDC-based temperature forecast ideal was then expanded to forecast 7 and 14-day future temperatures, and its RMSE was associated to the other models. In Table 4 and Figure 4 mentions the Comparative analysis of 80% 20% on Proposed with various existing algorithms. In this procedure we compare the results of RMSE and MBE values.

Table 5. Compare the RMSE and MBE of the temperature predictions made for 7 and 14 days in advance.

	RMSE		**MBE**	
Model/Day	**7**	**14**	**7**	**14**
RNN	3.15	3.61	-2.08	-3.26
LSTM	3.05	3.21	0.93	1.68
PDC	2.81	3.06	0.41	-0.79

Table 5 shows the tendency for this long-period temperature forecast to reduce RMSE and MBE. Refinement of the proposed model resulted in an RMSE of 3.06 for 14-day forecasts, which was lower than the RNN's 14-hour prediction RMSE.

5. Conclusion

DL-based temperature prediction model was suggested in this study to track temperature dissimilarities from 6 h to 14 d time periods by considering the important weather variables. A PDC network was used to fit the time-series data into the model. A PDC framework comprising temperature, and wind direction was used to refine the missing data, which frequently occurs in the collected weather record. Then an experimental PDC-based temperature forecasting method, such as 7 and 14 days, was used to test the model. Each neural network model's RMSE, or root-mean-square error, between actual and forecast temperatures was also assessed. In addition, the missing data in this research was refined using weather data such as wind direction. It is our goal to develop a temperature prediction model that incorporates additional meteorological variables such as soil temperatures and aerosols in the future. That is to say, a PDC will use all of the available meteorological data as input features and act as a temperature predictor and missing data refiner at the same time.

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