Forecasting Weather using Deep Learning from the Meteorological Stations Data : A Study of Different Meteorological Stations in Kaski District, Nepal

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Abstract

Contemporarily, one of the most pressing concerns is reliable and rapid weather forecasting. In Nepal, the Department of Hydrology and Meteorological uses a numerical modeling approach to forecast the weather, which is tardy and requires high end equipment to process the information so deep learning approach will be best alternative. This project aims to forecast the next 2-hour Precipitation and Air Temperature for Pokhara Domestic Airport meteorological station and next day Precipitation, Maximum and Minimum air Temperature forecast for Lumle, Begnas and Lamachaur meteorological station, total of four meteorological stations of the Kaski District, Nepal using Long Short-Term Memory (LSTM): a Recurrent Neural Network (RNN) and deploy the outputs through the web portal. The four hourly parameters: Rainfall, Relative Humidity (R.H), Wind Speed and Air Temperature were used for modeling the airport station forecast whereas Rainfall, Relative Humidity (R.H), Maximum and Minimum Temperature were used for modeling the Begnas and Lumle station forecast and only Precipitation data was used for Lamachaur station. Averaging and linear interpolation techniques were used to fill out the missing values and outliers were detected using Box Plot and replaced with threshold value for each parameter. Stochastic Gradient Descent and Adam optimizer are used to optimize the LSTM model. Among all the models prepared, Root Mean Square Error (RMSE) values range from 0.58 to 4.08 for precipitation model and from 0.16 to 0.82 for air temperature model and Mean Absolute Error (MAE) values range from 0.21 to 2.87 for precipitation model and from 0.12 to 0.64 for air temperature model were the values of the final model that indicates better accuracy for air temperature. The R^2 values range from 0.89 to 0.99 indicating the train and test data were fitted to the model really well.

Data, Modeling and Weather Portal codes can be accessed via GitHub repository: Modeling, Weather Portal

Keywords: weather forecast; deep learning; Long Short-Term Memory (LSTM); meteorological data; precipitation; air temperature .

1 Introduction

Weather is defined as persistent, multidimensional, dynamic and data intensive process ((Kaur and Singh, 2021)), which shows the atmospheric status of earth at different time and place. By knowing the weather extremities such as cyclone, thunderstorm, flooding, heavy rains ((NOAA, 2021)) in the past will help to avoid and mitigate them with less loss. In the context of Nepal, the 72- hour based short- range weather forecasting system was initiated by using Numeric Weather Prediction (NWP) system and has been delivering a periodical Climate Bulletin to the public through its website (https://www.dhm.gov.np/bulletins) ((DHM, 2023)). In Nepal, observed weather parameter was provided by 6 aero-synoptic, 9 synoptic, 20 sediment, 22 agro meteorological, 68 climatic 154 hydro-metric and 337 precipitation stations ((Karki, 2010)).

Due to the diverse change in geological terrains, rapid urbanization and the climate change, the prediction of the precipitation is getting more complex and high chances of containing ambiguity (Kucera et al., 2013). Precipitation prediction plays an vital role in the simulation of hydrological activity so to predict the precipitation to analysis several geomorphological activities (Wu et al., 2012) is also an vital application. Melting the glaciers in the Himalayas, probabilities of extreme weather conditions, several natural disasters may occur due to the rising temperature (Bošnjaković, 2012) which is so devastating. Air temperature plays a crucial impact to measure the greenhouse effect, solar radiation estimations, air pollution (Li et al., 2013; Immerzeel et al., 2010) and so many effects, so by knowing it primarily help to mitigate the various problems. Machine learning is artificial intelligence type that can help to make predictions based on new data without needing human help. (Bochenek and Ustrnul, 2022) mentioned Artificial Intelligence (AI) have largely supplanted the traditional Numerical Weather Prediction (NWP) forecasting approach, which had been followed by Nepal. Various research have been done for predicting the daily, monthly and annually rainfall prediction by using the data mining techniques (Kusiak et al., 2012; Chowdari et al., 2015; Tharun et al., 2018), machine learning algorithms (BABU, 2022; Basha et al., 2020; Liyew and Melese, 2021) and so many deep learning algorithms and methods (Hewage et al., 2019; Kang et al., 2020; Gamboa-Villafruela et al., 2021; Caseri et al., 2022) as well as several works have been done for air temperature too. Most of the research have been done on predicting the daily (Ustaoglu et al., 2008; Murat et al., 2018; Lin et al., 2021) and very few research have been done prediction on hourly temperature using machine learning and deep learning techniques (Shah, 2021; Carrión et al., 2021; Hou et al., 2022). There were several research (Hou et al., 2022; Hewage et al., 2019; Huang et al., 2019)) which conclude among machine and deep learning, to predict air temperature or precipitation by using sequential or time series data, deep learning; particularly Recurrent Neural Network type Long Short Term Memory (LSTM) gives the more precise and accurate result. On basis of these research findings, we use LSTM to model the forecasting precipitation and temperature among the different stations. As much as co-variate parameters available, the result is significantly improved (Ji et al., 2018).

Weather forecasting maintains the quality of life by mitigating the economic crisis and promoting better public health. The safety and well-being of humanity are highly impactable by weather changes (Lazo et al., 2020). RNNs are explored for meteorological time series (Ramos et al., 2019) and uses feedback connections that enable them to retain data that is previously fetched into their architecture.The architecture of RNN has a limitation of its inability to learn and make long-term forecasts (Ni et al., 2020).Long short-term memory (LSTM) is a type of ANNs with memory cells that control the flow of information into and out of its cells, which have been created to overcome limitations of RNN (Greff et al., 2016). (Yunpeng et al., 2017) suggests that LSTM is superior to other neural networks for multi-step ahead predictions. The main objective of this research is to fit the parameters into the LSTM model and with the help of this model, forecasting the precipitation and air temperature of the stations using time series forecasting of deep learning approach. The basic workflow for this project is collection of dataset, preprocess this dataset to make applicable to feed into the model and fit this dataset into the model with different layers and hyperparameters. The figure 1 gives the figurative insights of this project workflow.

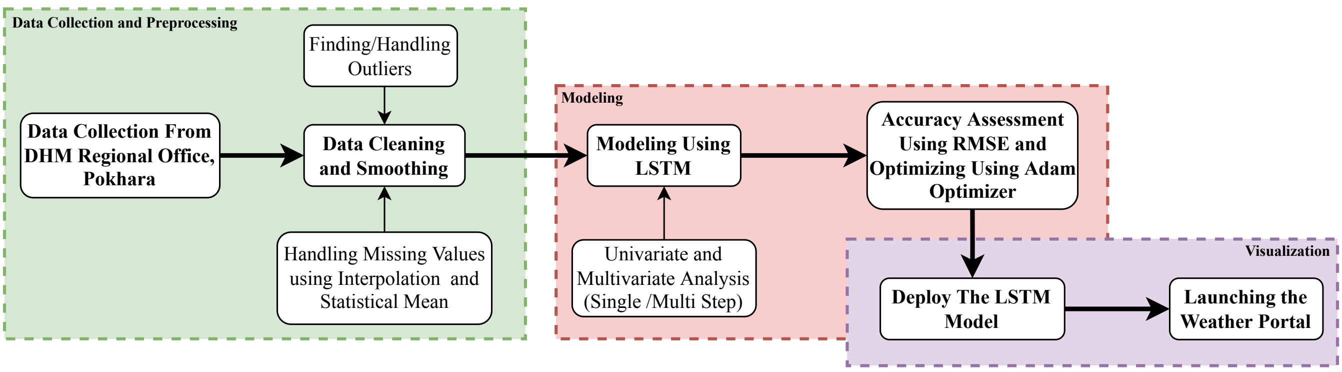

Figure 1: The methodology followed in this research.

2 Materials and Method

2.1 Study Area

Kaski is located at latitude 28°18′19″ N and 84°4′37″ E with an altitude varies from lowest land ranges from 450 meters to highest Himalayan range of 8091 meters (Basnet et al., 2020). Pokhara is an administrative headquarter of Kaski district which covers an area of 2,017 square km. In general, a lot of rain falls from May to September, among which the wettest month is July and driest month is November with 402 mm (15.8 inches) and 9 mm (0.4 inches) of precipitation respectively whereas the annual average precipitation of Kaski is 1620 mm (63.8 inches). Similarly, the average annual maximum and minimum precipitation ranges between 20° Celsius and 7° Celsius, June being the warmest month with 25° Celsius on average and January being the coolest month with 12° Celsius on average (Weather and Climate, 2023). The study stations are visualized on figure 2.

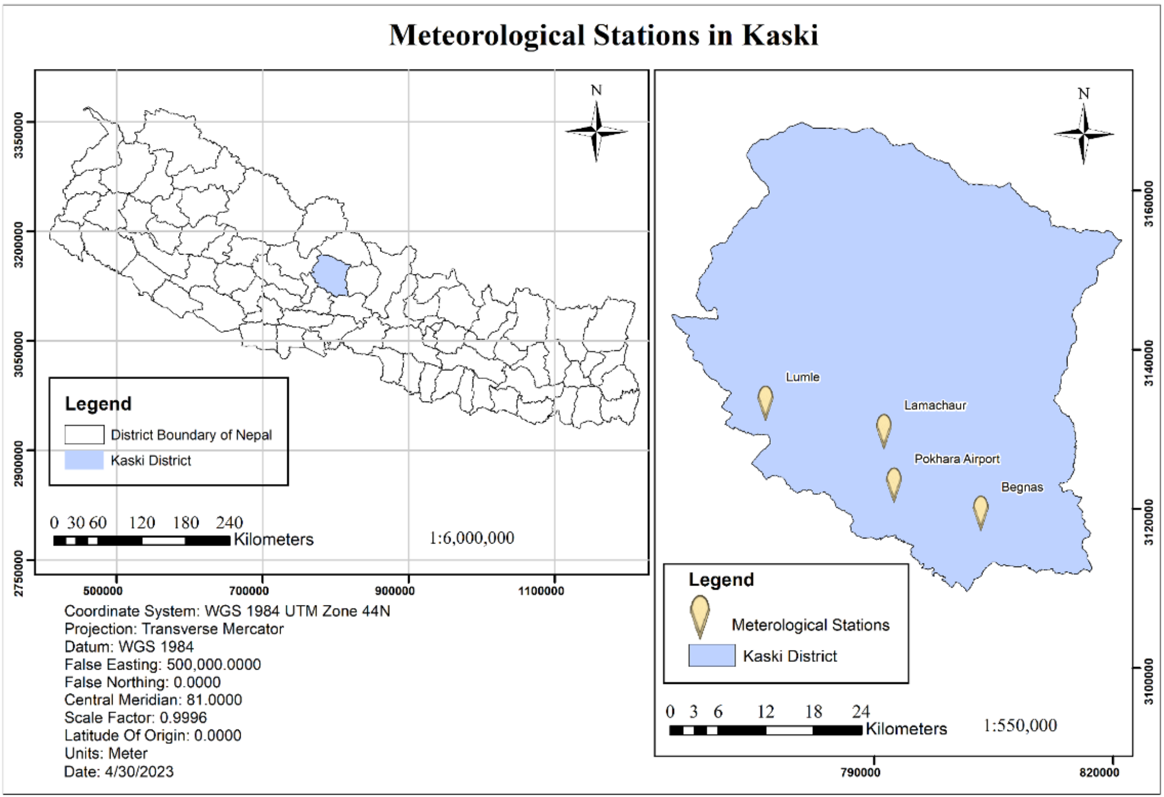

Figure 2: Study Area Map of Meteorological Stations in Kaski District.

Geographic coordinates of the meteorological stations of the study area are shown in table 1.

Table 1: Stations Geographic Details.

SN	Stations Name	District	Latitude	Longitude	Elevation(m)
1	Pokhara Domestic Airport	Kaski	28.20	83.97	827
2	Lumle Station	Kaski	28.29	83.81	1738
3	Begnas Station	Kaski	28.16	84.08	682
4	Lamachaur Station	Kaski	28.26	83.96	991

2.2 Dataset

The past weather dataset of four stations were collected from meteorological regional office Pokhara, Kaski. Pokhara Domestic Airport only has dataset of hourly temporal resolution and rest of other station were limited with daily dataset. The entire dataset used in this research is mentioned in table 2 where the station type, the period of time that we take for the modeling and information of parameters of the respective station were clearly mentioned.

Table 2: Descriptions of Dataset of Different Meteorological Stations used in this study.

SN	Stations Name	Station Type	Frequency	Parameters	Period	Num. of Dataset
1	Pokhara Airport	AeroSynoptic	Hourly	Precipitation(mm), Air Temperature (d. C), R.H(%), Wind Speed(m/s)	From 2019-11-11 To 2023-04-16	30051
2	Lumle Station	Agro Meteo-rological	Daily	Precipitation(mm), Max. and Min. Temperature (d. C), R.H(%), Wind Speed (Knot)	From 2010-01-01 To 2023-04-16	4852
3	Begnas Station	Climatological	Daily	Precipitation(mm), Max and Min Temperature (d. C), R.H(%)	From 2010-01-01 To 2022-12-31	4749
4	Lamachaur Station	Precipitation	Daily	Precipitation(mm)	From 2010-01-01 To 2023-04-16	4852

The sample dataset which had used for the modeling to forecast was mentioned in table 3 and table 4.

Table 3: Sample Hourly data of Pokhara Domestic Airport Station.

Time Stamp	Precipitation (mm)	Air Temperature (°C)	Relative Humidity (%)	Wind speed (m/s)
11/11/2019 6:00	0	23.4	69.399	2.4
11/11/2019 7:00	0	24.3	64.7	2.5

Table 4: Sample Daily Dataset of Begnas, Lumle, and Lamachaur Meteorological Station

Time Stamp	Sample Data of Begnas and Lumle Station				Lamachaur
	Precipitation (mm)	Maximum Temperature (°C)	Minimum Temperature (°C)	Relative Humidity (%)	Precipitation (mm)
01/01/2015 3:00	0	15	8	32.9	0.0
02/01/2015 3:00	29	12.5	7	95.9	19.6

All the timestamp mentioned in dataset are in UTC (GMT+5:45) format.

2.3 Data Preprocessing

The original dataset contained 4.85% of missing data (precipitation 2.289290%, air temperature 1.087413%, relative humidity 1.083597%, wind speed 1.09122%) in the hourly data set. Similarly, in Begnas station 4.28% of data was found missing and in Lumle and Lamachaur station contain few number of missing data. The outliers were detected using the boxplot and replace these outliers by using pandas with the threshold value which was assume by analyzing the boxplot. Linear interpolation is applied for missing value treatment whereas in case of missing precipitation, fill with zero. The comparison between before and after removing noise data using box plot of Pokhara airport data as a sample shown in the figure 3. In figure 3(a), the dataset contains noises and this affects the outcome so need to omit this dataset. So as a result 3(b), which was created by applying threshold, it contains no noise data.

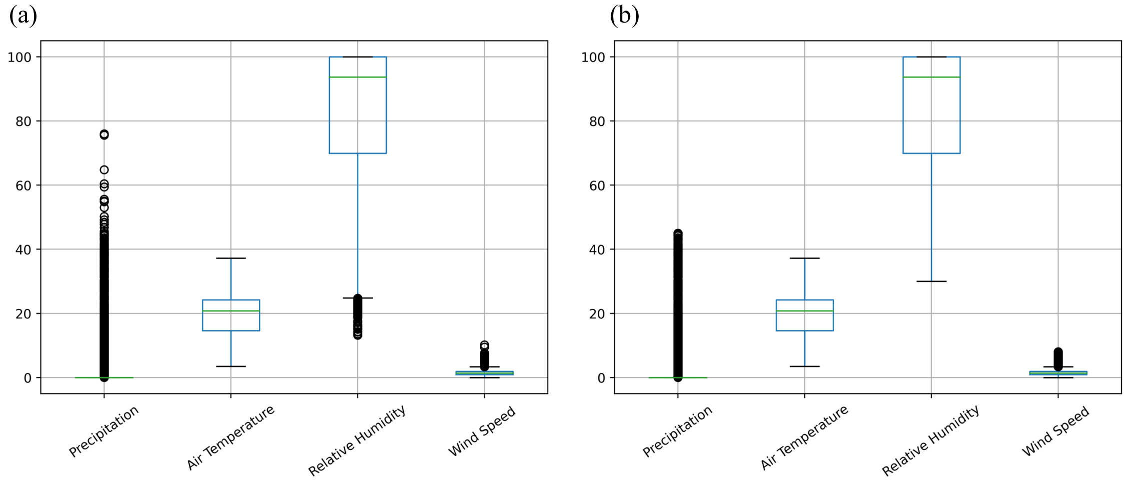

Figure 3: (a) contains the noise and (b) contains without noise data of Pokhara Domestic Airport hourly dataframe.

The correlation among the different parameters does impact on the forecasting. Figure 4(a) shows the impact of wind speed and relative humidity are more influencing whereas for daily station parameter i.e. figure 4 (b) and figure 4 (c), minimum temperature and relative humidity influences more. (Pathan et al., 2021) also concludes the windspeed and minimum temperature has a significant impact on forecasting the rainfall.

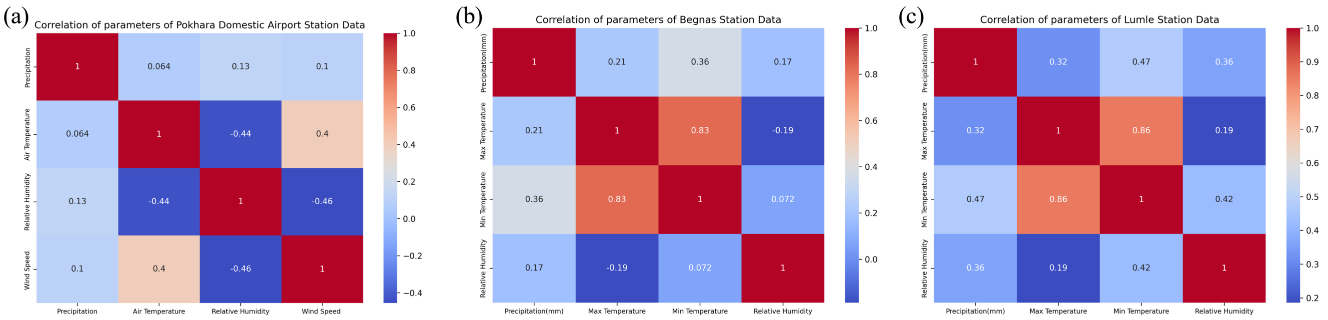

Figure 4: Correlations between the parameters in respective meteorological station containing several parameters.

2.4 Modeling using Long Short-Term Memory (LSTM)

2.4.1 Architecture of Model

Long Short-Term Memory (LSTM) is an artificial neural network used in deep learning. Artificial Neural Network (ANN) is used for forecasting because of its versatility and capabilities based on past knowledge (Siami-Namini et al., 2018). LSTM includes the layer of gates (the cell state 4 is managed by the input gate 1 and forget gate 2, which is long term memory and the output gate 3 produces the output vector 5 which is the memory system that enables to remember long time) that allows the passing of data through a multi-step process to enable the recognition of patterns (Petneházi, 2019).

$$i_t = \sigma(W_{ix}x_t + U_{ih}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{fx}x_t + U_{fh}h_{t-1} + b_f) \tag{2}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(W_{cx}x_t + U_{ch}h_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(W_{ox}x_t + U_{oh}h_{t-1} + b_o) \tag{4}$$

$$h_t = o_t \cdot \tanh(c_t) \quad (5)$$

The hourly precipitation and average air temperature for Pokhara Airport station was modeled using multivariate multistep LSTM while daily precipitation, minimum and maximum air temperature for Lumle and Begnas station were modeled using multivariate LSTM and daily precipitation of Lamachaur station was modeled using univariate LSTM. All the dataset were normalized using the respective scaler as shown in the table 5 and the training testing dataset were splitted in the ratio of 80:20 percentage which is 24021 and 6005 training and testing datasets respectively for Pokhara airport hourly data whereas 70:30 percentage ratio was taken for rest of the daily data stations i.e., 3396 and 1456 training and testing datasets respectively. In the Pokhara airport station hourly modeling sliding window techniques was followed as it contains large number of dataset and passed 24 sets of data at once which contains all the parameters in normalized form to forecast the precipitation and air temperature for next 2 hours whereas in other daily forecast lag feature is introduced to the data frame as a new column which shift one day target data to the future and train the model with single day dataset to forecast the next day value. Lag feature are very inappropriate for processing temporal information like time series forecasting (Sattari et al., 2012) and it is the values of previous time step that will be valuable because it is based on the fact that what happen in past might impact or inherent the information to the future. Bidirectional LSTM was used for Pokhara airport hourly temperature modeling with adam optimizer and rest of other uses stacked LSTM with Stochastic Gradient Decent (SGD) optimizer used. Table 5 contains all the details of the prepared nine models of precipitation and air temperature four stations.

Table 5: Final modeling details of all station weather models.

Models	Trainable Parameters	Normalization Scaler	Layers	Optimizer
Pokhara Airport Hourly Temperature	332,034	StandardScaler	Bidirectional LSTM	Adam (learning rate=.001)
Pokhara Airport Hourly Precipitation	1,208,641	MinMaxScaler	LSTM	SGD (momentum=0.95)
Lumle Minimum Air Temperature	1,130,657	MinMaxScaler	LSTM	SGD (momentum=0.9)
Lumle Maximum Air Temperature	1,130,657	MinMaxScaler	LSTM	SGD (momentum=0.9)
Lumle Precipitation	89,249	MinMaxScaler	LSTM	SGD (momentum=0.9)
Begnas Minimum Air Temperature	89,249	MinMaxScaler	LSTM	SGD (momentum=0.95)
Begnas Maximum Air Temperature	89,249	MinMaxScaler	LSTM	SGD (momentum=0.95)
Begnas Daily Precipitation	30,881	MinMaxScaler	LSTM	SGD (momentum=0.85)
Lamachaur Precipitation	88,225	MinMaxScaler	LSTM	SGD (momentum=0.8)

Figure 5 shows the performance of hourly air temperature and precipitation models on training and testing data. Similarly figure 6, figure 7 and figure 8 indicates the model performance on Begnas and Lumle minimum, maximum air temperature, precipitation and Lamachaur precipitation model respectively. Overall the prediction value are pretty close to the original one so the performance of the model is good.

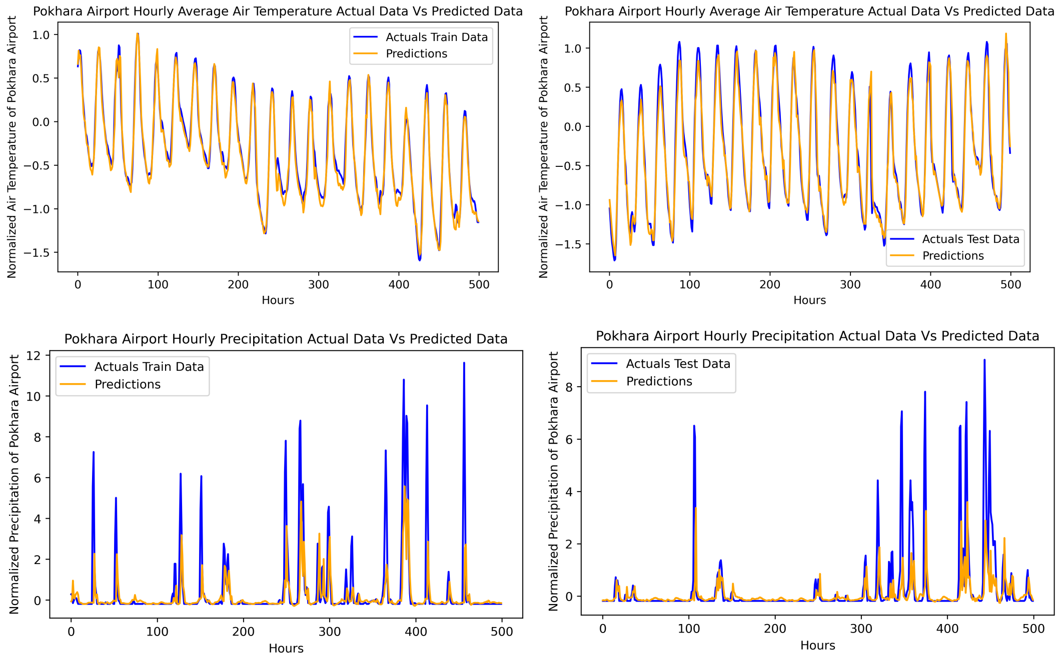

Figure 5: Air temperature and precipitation model performance of Pokhara domestic airport on training and testing data.

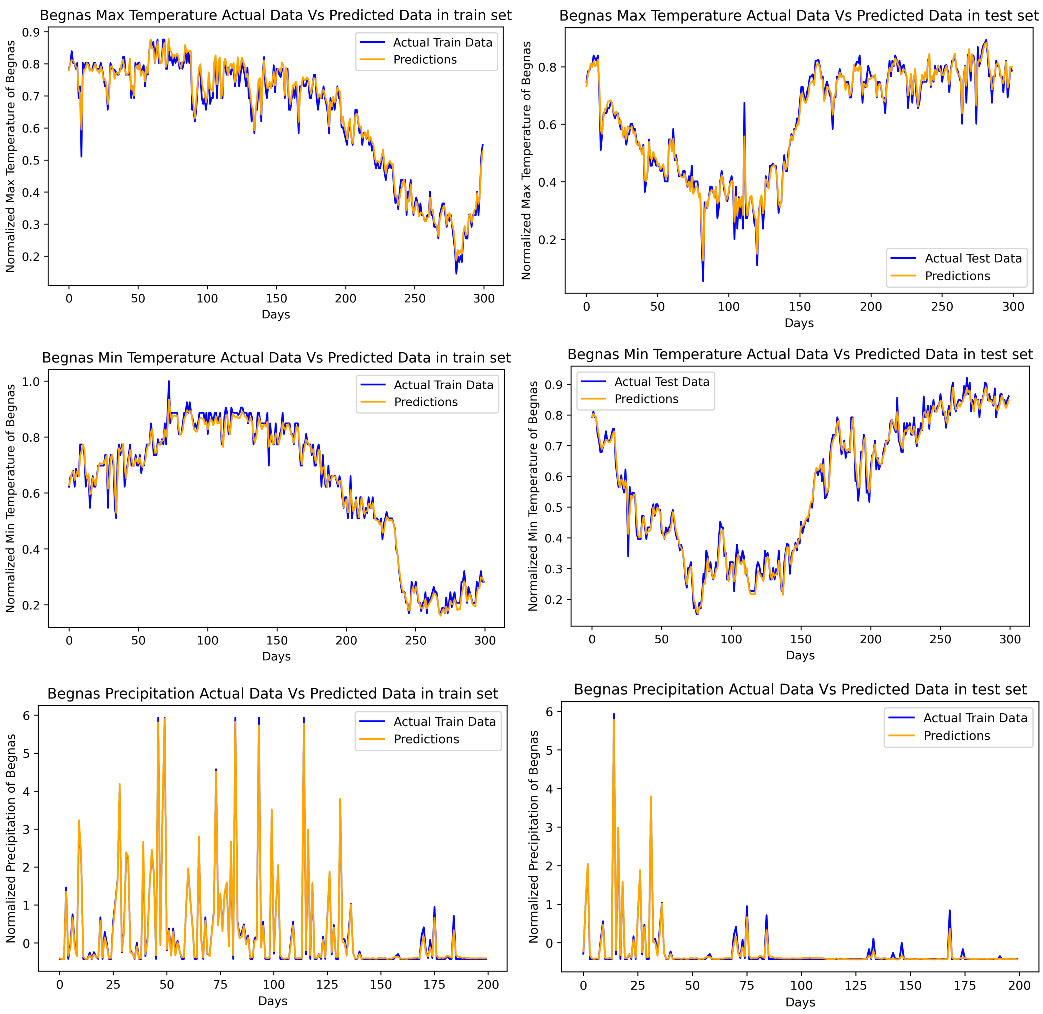

Figure 6: Maximum and minimum air temperature and precipitation model performance of Begnas station on training and testing data.

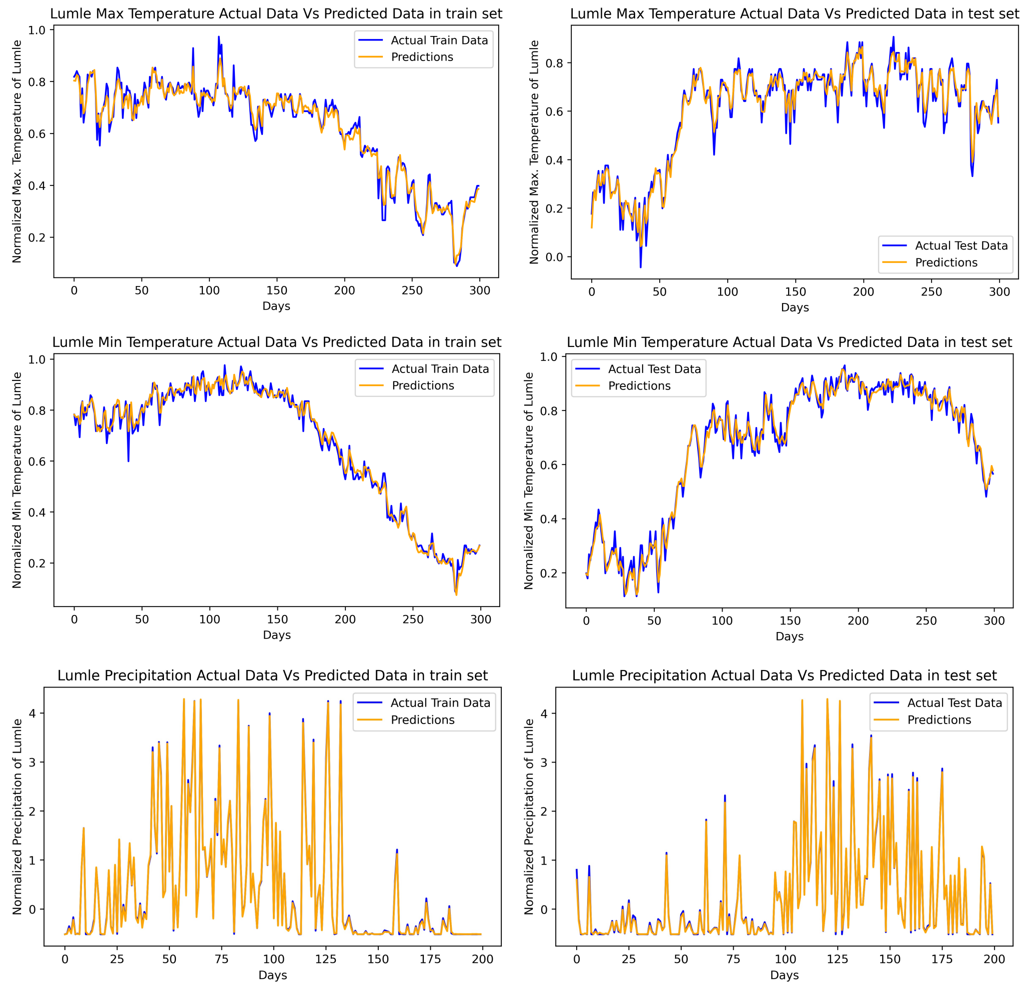

Figure 7: Maximum, minimum air temperature and precipitation model performance of Lumle station on training and testing data.

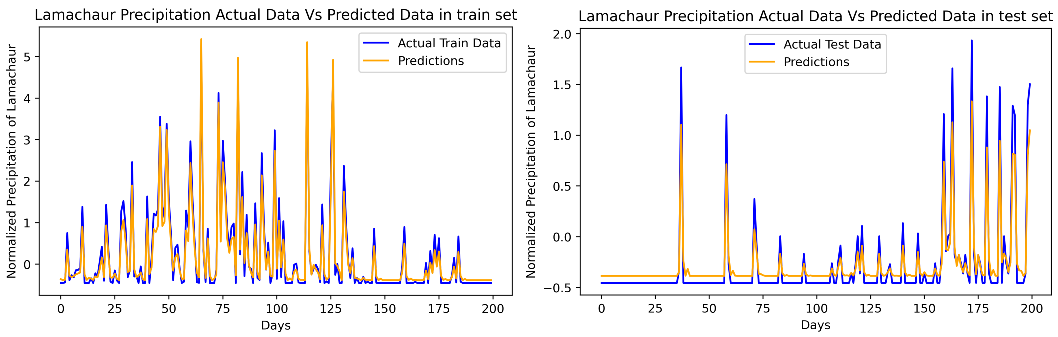

Figure 8: Precipitation model performance of Lamachaur on training and testing data.

2.4.2 Evaluation of Model Performance

The Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the R squared metrics were used to evaluate the performance of the model according to the predicted and the measured values from the LSTM model. The square root of averages squared differences between actual and predicted observation is RMSE, MAE means average absolute errors between actual and predicted values whereas R squared measures the extent of variance that how the independent variable of the model able to relate the dependent one.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(a_j - b_j)^2} \tag{6}$$

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}|a_j - b_j| \tag{7}$$

$$R^2 = 1 - \frac{\text{Sum of Squares of Residuals}}{\text{Total Sum of Squares}} \tag{8}$$

Where a_j represents the actual value, b_j represents the predicted value, and n is the number of samples.

Adam optimizer was used for the Pokhara airport hourly temperature model and for rest of the model Stochastic Gradient Decent (SGD) was used with different momentum value which is mentioned on table 5.

2.5 Deploying the Model

A combination of programs and frameworks, including Flask for the backend and React JS for the frontend, have been used to develop a weather portal. Users can access the results by using the web application. The final model is downloaded in hierarchical data format(h5) and they were then loaded into the Flask server along with each station's observational data in CSV file format. The necessary variables and lags were taken from the observational data and stored in a CSV file to prepare the data for prediction. The prediction data was standardized using respective scaler mentioned in table 5. After normalizing the input data, it was fed to the model to provide normalized output, which was then inversely converted to produce denormalized findings. Users were then able to simply receive information about the projected temperature and precipitation for their area of interest. The web application is static since the database consisting weather parameters used to predict temperature and precipitation is limited for a given timestamp. However, it can be made dynamic by feeding the newly observed data from the meteorological stations to the database, which either can be done manually editing to the CSV file or pegging the database with the official DHM's data, latter one being more systematic.

3 Result and Discussion

The hourly precipitation and air temperature for Pokhara Airport station were modeled while daily precipitation, minimum and maximum air temperature for Lumle, Begnas station and daily precipitation of Lamachaur station were modeled using LSTM. The prediction performance evaluation metrics for the modeled LSTM algorithm, RMSE and MAE were defined and R squared value was defined to evaluate the overall fit of the data into the model. Table 6 represents the predictive power of different models in terms of RMSE and MAE for both train and test data along with the R squared value for each model's train and test data.

Among the models, precipitation of Lamachaur station had a high value of Root Mean Square Error (RMSE) of 4.08 and Mean Absolute Error (MAE) of 2.87 on test data because it was modeled with only one parameter i.e precipitation, followed by Lumle and Begnas precipitation model due to high variation of precipitation patterns. Complex nature of precipitation and it's dependencies on variety of factors plays a significant role for weak predictive power because of which high magnitude of differences between actual and predicted values were observed in those models when compared to others. In contrast, the hourly precipitation of Pokhara Domestic Airport had a least RMSE and MAE value of 0.61 and 0.21 respectively on test data, which indicates the difference in magnitude of actual and predicted value of that station. The superior model performance was achieved in this case because the number of datasets that were used for Pokhara Domestic Airport were in large numbers than at other stations due to which model learnt the underlying precipitation patterns of this station more significantly.

Similarly, in terms of predicting temperature, hourly temperature of Pokhara Domestic Airport out-performed other models with RMSE and MAE value of 0.16 and 0.12. This is due to the fact that temperature, more or less follows the seasonal patterns making it easier to understand the flow of trends for an algorithm along with the provision of larger number of datasets to detect seasonal change. Minimum and maximum surface air temperature of Lumle and Begnas stations were predicted with the RMSE score of 0.58 and 0.82 (Lumle) and 0.58 and 0.66 (Begnas). The MAE scores were 0.46 and 0.64 for Lumle and 0.36 and 0.47 for Begnas station.

The measure of R squared value describes fit rather than forecast accuracy, all the models fit to the model very accurately with the actual data. Closer it's value to 1 means it's performing better. The values range from 0.89 to 0.99 indicating that the relationships between input and target variables were captured accurately maintaining a good fit into the model.

Table 6: Final modeling details of all station weather models.

Models	RMSE		MAE		R Squared	
	Train	Test	Train	Test	Train	Test
Airport Hourly Temperature	0.12	0.16	0.077	0.12	0.98	0.96
Airport Hourly Precipitation	0.78	0.61	0.27	0.21	0.92	0.89
Lumle Minimum Temperature	0.62	0.58	0.47	0.46	0.98	0.99
Lumle Maximum Temperature	0.79	0.82	0.6	0.64	0.96	0.96
Lumle Precipitation	2.16	2.34	1.36	1.52	0.99	0.98
Begnas Minimum Temperature	0.57	0.58	0.42	0.36	0.98	0.99
Begnas Maximum Temperature	0.69	0.66	0.51	0.47	0.98	0.98
Begnas Daily Precipitation	1.55	1.81	0.99	1.15	0.99	0.99
Lamachaur Precipitation	3.78	4.08	2.73	2.87	0.97	0.97

Analyzing the results from table 6 , it is seen that errors in predictions of temperature are relatively lower than in predictions of precipitation of a same meteorological station. This is due to the fact that temperature follows seasonal patterns that can be easily understood by deep learning algorithms while precipitation comprises a complex nature with more inter dependencies parameters such as wind speed, wind direction, atmospheric pressure, etc. This makes the accurate prediction of precipitation is more challenging, however, the accuracy can be increased provided that most of the influencing factors for precipitation are taken into account during the data collection process. Unfortunately, the variables recorded in the stations of interest by the DHM did not include a variety of factors responsible for rainfall which eventually becomes the shortcoming of the project.

Table 7: Actual VS Predicted values of Pokhara Domestic Airport Station.

Model	Actual Value	Predicted Value	Time Stamp
Pokhara Airport Hourly Precipitation	0	0.031	2023-04-16 7:00
Pokhara Airport Hourly Precipitation	0	0.01	2023-04-16 8:00
Pokhara Airport Hourly Temperature	30	29.5	2023-04-16 7:00
Pokhara Airport Hourly Temperature	30.2	29.8	2023-04-16 8:00

Table 8: Actual VS Predicted values of Pokhara Domestic Airport Station.

Model	Actual Value	Predicted Value	Date
Begnas Daily Precipitation	0	0.078	2022-12-31
Begnas Daily Maximum Temperature	19	18.65	2022-12-31
Begnas Daily Minimum Temperature	8.5	7.9	2022-12-31
Lumle Daily precipitation	0	0.043	2023-04-14
Lumle Daily Maximum Temperature	26	25.4	2023-04-14
Lumle Daily Minimum Temperature	14.2	13.4	2023-04-14
Lamachaur Daily Precipitation	0	1.46	2023-04-16

We have predicted the air temperature and precipitation of the stations using the final model and compared them with the actual observed data of that predicted date as shown in the table 7 (a multi-step forecasting of next 2 hour) and table 8 (a single step forecasting). It provides a specific knowledge about an accuracy of the proposed models as the numeric values of predicted output can be compared with the actual observed value at the station. As our objective is to predict the next 2 hour forecast of air temperature and precipitation for Pokhara domestic airport meteorological station and next one day forecast for Lumle, Begnas and Lamachaur meteorological stations, it was thus achieved with an acceptable results.

4 Conclusion and Recommendation

The precipitation and temperature of all four stations have been modeled using LSTM with different numbers of hidden layers, neurons, and optimizers as well as best suited activation function. The results of the project indicate that the accuracy of the machine learning models can vary significantly depending on the quality and quantity of the datasets and the parameters or variables used in the model. Among the stations, Lamachaur station only contains precipitation parameters, on the basis of this single parameter the model of predicting next day precipitation data using univariate LSTM has more error followed by Lumle, Begnas and Pokhara Domestic Airport. Although all models fit well for training and testing data based on R2 value, Pokhara Airport has short temporal resolution of hourly dataset and a high number of datasets so compared to other station models, particularly Pokhara Airport's precipitation and air temperature model performs very well in terms of error analysis and all the outputs are deployed through the weather portal. Rather than using complex and tedious Numerical Weather Prediction (NWP), the Machine Learning approach will be the best alternative for the short computational time with efficient results. Based on the findings and complete deployment of the project following are the recommendations for increasing the accuracy of overall project.

1. Integration of additional weather parameters like due points, cloud state, wind direction, atmospheric pressure and so on makes the prediction more precise.

2. The use of more dataset will capture the long-term dependencies of weather patterns which helps to give better results.

3. Before using all the historical dataset, calibration of raw data will be highly recommended to know about the biases and errors on the original dataset itself after which it will perform well on the model.

4. Incorporate ensemble forecasting will give more precise results.

5. Further research and studies can explore other machine learning algorithms to improve the model accuracy.

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Author Contributions

Supath Dhital has done conceptualization of project, modeling, discussions and conclusions, writing manuscript and handling the visualization of graphs. **Kapil Lamsal** has helped with the web deployment of weather portal, researching the background introduction, discussions, writing and screening the paper. **Sulav Shrestha** has helped by doing the preprocessing tasks on data, explore the background study and checking the suitability of the model. **Umesh Bhurtyal** is the entire project supervisor so timely discussions, reviewing, editing and guiding during whole project.

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